

T.C.
İSTANBUL KÜLTÜR UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

**ANALYZING THE EFFICIENCY OF AI INTEGRATION FOR PROJECT
MANAGEMENT EMPLOYING DEA: A CASE STUDY FOR A DATA
CENTER**

MASTER'S THESIS
MUATH QANNITA
1900005592

Department: Industrial Engineering

Program: Engineering Management

Supervisor: Assist. Prof. Zeynep GERİN

JUNE 2025

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Muath Qannita

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LIST OF SYMBOLS

X_{1i} represents **input** (cost) for project i.

X_{2i} represents **input** (time) for project i.

Y_i represents **output** (quality level) for project i.

λ_j are the DEA multipliers that determine the contribution of each DMU in forming the efficiency frontier.

θ is the efficiency score of the project, where $0 \leq \theta \leq 1$



Üniversite	: İstanbul Kültür Üniversitesi
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ÖZET

Veri Zarflama Analizi (DEA) Kullanılarak Proje Yönetiminde Yapay Zeka Entegrasyonunun Verimliliğinin Analizi: Bir Veri Merkezi Üzerine Durum Çalışması

Muath Qannita

Yapay zeka (YZ) iş yüklerinin dijital ekonomide hızla yaygınlaşmasıyla birlikte, veri merkezlerinin bu yüksek hesaplama gücü gerektiren taleplere uyum sağlayacak şekilde altyapılarını ve operasyonel modellerini yeniden şekillendirmeleri gerekmektedir. Bu tez, 1 MW kapasiteli bir veri merkezi ortamında YZ iş yükü entegrasyonunun verimliliğini değerlendirmek amacıyla yapılandırılmış bir proje yönetimi yaklaşımı uygulamakta ve performansı maliyet, zaman, kalite ve yatırım getirisi (ROI) boyutlarında ölçmek için Veri Zarflama Analizi (DEA) yöntemini kullanmaktadır. Çalışmada üç farklı iş yükü senaryosu analiz edilmiştir: Seçenek 1 (YZ'siz), Seçenek 2 (%20–30 YZ), Seçenek 3 (%50 YZ). Başlangıç DEA sonuçları, YZ destekli yapıların kaliteyi sınırlı ölçüde artırsa da, artan maliyet ve proje süresi nedeniyle genel verimliliği düşürdüğünü göstermektedir. İki ek senaryo analizinde ise; (1) artan YZ altyapı maliyetlerinin etkisi ve (2) ROI'nin çıktı faktörü olarak dahil edilmesi incelenmiştir. Bulgular, YZ seçeneklerinin yalnızca yüksek ROI sağlandığında ve hızlı geri dönüş süresiyle verimli hale geldiğini göstermektedir. Sonuç olarak, en verimli strateji; kapasitenin %80–90'ını geleneksel iş yüklerine, %10–20'sini ise ölçeklenebilir YZ uygulamalarına ayırmaktır. Bu hibrit yaklaşım, mevcut verimliliği korurken geleceğe uyum sağlar. Çalışma, proje yönetimi ile DEA yöntemini entegre ederek

veri merkezi tasarımı ve iş yükü planlaması için karar vericilere uygulanabilir bir çerçeve sunmaktadır.

Anahtar Kelimeler: Veri Merkezi, Yapay Zeka, Proje Yönetimi, DEA, ROI, Verimlilik, YZ İş Yükü Entegrasyonu



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ABSTRACT

Analyzing the Efficiency of AI Integration for Project Management employing DEA: A Case Study for A Data Center

Muath Qannita

As artificial intelligence (AI) workloads continue to expand in the digital economy, data centers must adapt their infrastructure and operational models to support these computationally intensive demands. This thesis evaluates the efficiency of AI workload integration in a 1 MW data center environment by applying a structured project management approach and using Data Envelopment Analysis (DEA) to assess performance across cost, time, quality, and return on investment (ROI) dimensions. Three workload scenarios are analyzed: Option 1 (no AI workload), Option 2 (20–30% AI workload), and Option 3 (50% AI workload). The baseline DEA results show that AI-enhanced configurations slightly improve quality, result in substantially increased costs and extended project timelines, thereby diminishing overall operational efficiency. To further explore this trade-off, two scenario analyses are conducted: (1) evaluating efficiency under increasing AI infrastructure costs, and (2) introducing ROI as an additional output factor. The findings show that AI options remain viable only when ROI is high and breakeven is achieved within a short time frame due to the fast pace of technological change. The study concludes that the most efficient and future-resilient strategy is to allocate 80–90% of capacity to traditional workloads and 10–20% to scalable AI deployments. This hybrid approach balances current

efficiency with long-term adaptability. The research contributes a practical framework for decision-makers by integrating DEA with project management principles to guide data center design and workload planning.

Keywords: Data Center, Artificial Intelligence, DEA, ROI, Project Management, Efficiency, AI Workload Integration



1. INTRODUCTION

Data centers are critical infrastructures supporting the digital economy, providing the computational power and storage required to run diverse applications, from cloud services to high-performance computing. As the demand for data processing continues to grow, managing the complexity of data center operations has become increasingly challenging. Effective project management plays a vital role in the successful design, construction, and operation of data centers by ensuring that resources are efficiently allocated, timelines are met, and performance goals are achieved. With the rising integration of artificial intelligence (AI) workloads, data centers are under pressure to adapt both technically and financially. AI applications require specialized hardware, higher energy provisioning, and more advanced cooling systems, all of which introduce new operational and economic challenges. These factors emphasize the importance of robust project management and efficiency evaluation methodologies. In this context, Data Envelopment Analysis (DEA) serves as a valuable tool for measuring the relative efficiency of different data center design strategies by comparing multiple input and output variables, such as cost, time, quality, and return on investment (ROI). This research investigates whether integrating AI workloads into a 1 MW data center in Iceland configuration is efficient from both a technical and economic perspective. The analysis is grounded in a case study model and employs DEA to compare several workload distribution options, including traditional (non-AI), hybrid (20–30% AI), and high-intensity (50% AI) designs. The study also incorporates scenario analysis to evaluate the impact of rising AI infrastructure costs and the inclusion of ROI as an output factor. The primary objectives of the research are to (1) assess current project management practices in data centers in relation to AI workload demands, (2) analyze the efficiency of different workload distribution strategies using DEA, and (3) provide practical recommendations for optimizing data center design under economic and technological constraints. The study specifically explores how the Waterfall project management methodology supports structured development in high-complexity infrastructure environments like AI-enabled data centers. The findings

reveal that while AI-integrated designs offer higher quality outputs, their efficiency significantly declines when rising costs and delayed ROI are factored in. The DEA results and scenario analysis suggest that the most efficient and resilient strategy involves allocating 80–90% of data center capacity to traditional (non-AI) workloads and reserving 10–20% for scalable AI operations, enabling gradual integration as technologies mature and costs stabilize. This research contributes to academic literature by bridging AI infrastructure planning, project management methodologies, and quantitative efficiency analysis. By applying DEA within a project management framework, the study delivers actionable insights for data center operators seeking to balance performance, cost, and adaptability in an evolving technological landscape. To address these goals, the thesis is structured into five main chapters: Introduction – outlining the topic, aims, and research questions, Literature Review – examining AI workloads, project management methods, and DEA applications, General Concepts – presenting core definitions and theoretical background, Methodology – detailing the DEA model and scenario design, and Implementation and Results – where findings are analyzed and discussed, followed by a final conclusion and future research directions.

2. GENERAL CONCEPTS

2.1. Data Center

Data centers are specialized facilities designed to house computer systems, storage solutions, and networking equipment essential for business operations. The study provides the necessary infrastructure for hosting applications, managing data, and delivering IT services (Arregoces & Portolani, 2003). Typically, data centers consist of various components, including servers, storage arrays, and networking hardware, all supported by robust power and cooling systems to ensure operational continuity and stability (Geng, 2014). The modern data center plays a pivotal role in handling growing digital demands, ensuring optimal infrastructure and workload management. For example, load balancing is critical to address increased traffic, with advancements such as Bit-based Collaborative Load Balancers (BCLB) enabling efficient resource utilization through collaborative switch inspection, reducing overhead while maintaining performance. Additionally, machine learning applications are integrated into data centers to enhance energy prediction and management, as demonstrated by hybrid models like LSTM-kNN, which improve forecasting accuracy and operational efficiency. Lastly, GPU sharing strategies, such as GPUColo, optimize server use by balancing training and inference jobs, reducing capital costs and increasing performance (Chen et al., 2024; Mogal et al., 2024; Yang et al., 2024).

2.2. Data Center Design

Designing a data center involves carefully balancing performance, security, and scalability requirements with considerations for cost-effectiveness and energy efficiency. Essential elements of data center design include:

Infrastructure Layout: The physical arrangement of servers, racks, and network equipment must optimize space utilization and airflow, facilitating efficient cooling and easy access for maintenance.

Power Supply and Backup: Data centers require uninterrupted power supply systems, typically featuring redundant configurations and backup generators to ensure resilience against outages.

Cooling Systems: Efficient cooling solutions, such as air or liquid cooling, are critical to maintain optimal operating temperatures, reducing energy consumption while extending the lifespan of hardware components (Wang et al., 2022)

Network Connectivity: Robust network architecture provides low-latency connections, high data transfer speeds, and security protocols that support diverse workloads and minimize downtime.

Security Measures: Physical and digital security measures safeguard the data center against unauthorized access, cyber threats, and physical risks. Common security features include biometric access, surveillance systems, firewalls, and advanced encryption (Geng, 2014).

Effective data center design addresses challenges like energy efficiency, carbon emissions, and resource optimization. For instance, green energy models prioritize sustainability by reducing reliance on non-renewable sources, while intelligent designs utilizing algorithms like supporting vector regression predict and manage energy consumption effectively. Furthermore, cutting-edge technologies like CXL over Ethernet address memory disaggregation, reducing latency and improving memory access efficiency. Smart layouts incorporating artificial intelligence optimize spatial and resource allocation, significantly enhancing the design process and operational efficiency (Lu & Li, 2024; Wu et al., 2023).

2.3.AI Workload Data Center

AI workload data centers are specifically optimized to handle the demanding computational and data processing needs of AI applications. Unlike traditional facilities, these data centers incorporate advanced hardware, such as Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs), to support intensive machine learning and deep learning tasks (Lu et al., 2023). These centers redefine operational standards by requiring specialized infrastructure to meet strict service-level objectives (SLOs) (Zilin et al., 2023). Generative AI workloads introduce unique challenges, requiring high-performance infrastructure to support tasks like content generation, language modeling, and image synthesis. These applications demand massive parallel processing, accelerated training, and low-latency inference to meet real-time or near-real-time requirements (Liu et al., 2024). Techniques like GPU Colo

enable the concurrent execution of training and inference tasks on shared GPUs, maximizing utilization while maintaining low latency. Intelligent scheduling and task migration strategies further enhance resource efficiency and workload management. Additionally, AI-driven design innovations, such as leveraging convolutional neural networks for state analysis, provide new methods to boost performance and operational efficiency in AI-focused environments (Chen et al., 2024).

2.4. Project Management

2.4.1. Project Management Objectives

One of the critical aspects of project management is achieving a balance between the three key scopes of the Quality Triangle: Cost, Time, and Scope. This relationship, known as the Iron Triangle or Triple Constraint, is central to ensuring that project objectives are met efficiently and effectively (Atkinson, 1999). These interdependent factors create a framework that guides project decisions and prioritization. Cost: Refers to the financial resources allocated for the project. Effective cost management ensures that the project remains within budget while still meeting its objectives (Pébay & Baker, 2003). Time: Denotes the project's timeline and deadlines. The timely completion of a project is a key measure of its success, but it must be balanced against scope and cost considerations (Wright & Lawlor-Wright, 2018). Scope: Represents the deliverables and the work required to achieve project goals. A well-defined scope is essential to maintaining clarity and alignment among stakeholders (Atkinson, 1999).

The quality of project deliverables is directly influenced by the interaction between these three factors. For instance, expanding the project scope often leads to increased costs and extended timelines, while reducing costs may result in a narrower scope or compromised quality (Pébay & Baker, 2003). This relationship highlights the importance of managing trade-offs to maintain equilibrium and deliver high-quality outcomes (Wright & Lawlor-Wright, 2018). In figure 2.1 below the quality triangle presented.

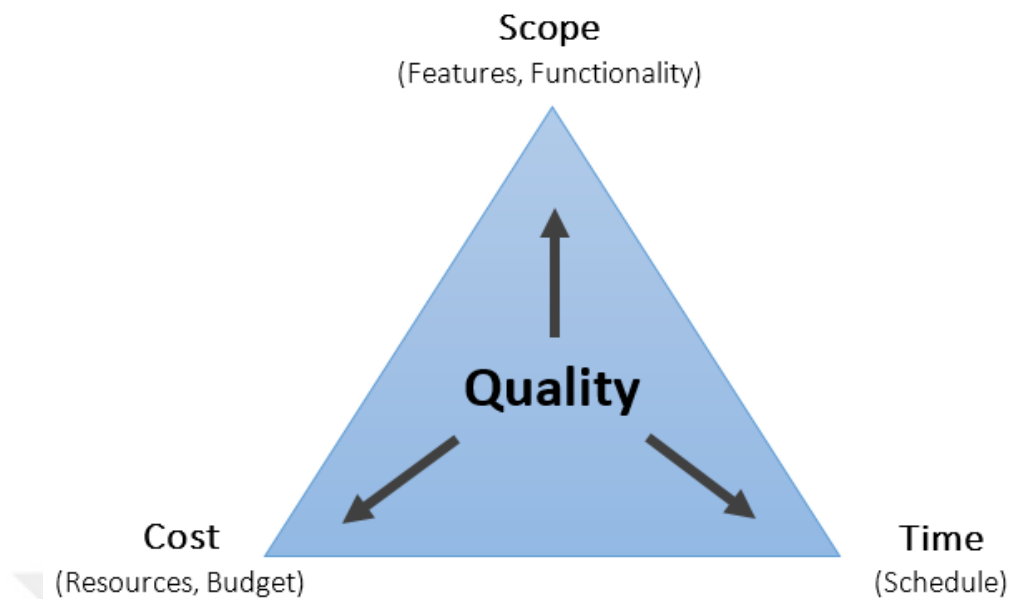


Figure 2.1: Quality triangle

2.4.2. Project Management Methods

Project management is founded on more than the execution of tasks or the achievement of milestones; it is a disciplined approach to planning, organizing, and directing resources to achieve clearly defined objectives. At its core, project management seeks to balance the critical constraints of cost, time, and scope while addressing the inherent complexities and uncertainties associated with diverse projects (Rudolph et al., 2008). Over the years, various methodologies have emerged to provide structured frameworks for managing projects more effectively and efficiently (Marion, 2018). These methodologies are designed to enhance collaboration, optimize resource utilization, and mitigate risks, allowing project teams to navigate the dynamic and often unpredictable nature of projects. By offering principles, processes, and tools, these approaches enable project managers to align project activities with organizational goals and stakeholder expectations. Whether emphasizing meticulous upfront planning or iterative cycles of refinement, project management methodologies are adaptable to the varied demands of different sectors and contexts (Petrocelli, 2020)

The Agile method is a flexible and iterative project management approach designed to adapt to evolving requirements and uncertainties. Unlike traditional linear methods, Agile emphasizes continuous collaboration, incremental progress, and responsiveness to change (Reifer, 2002). Rooted in the principles of the **Agile Manifesto**, it prioritizes

individuals, working solutions, and stakeholder collaboration over rigid processes (Cohen et al, 2004). Agile frameworks, such as Scrum and Kanban, break projects into smaller, manageable iterations, allowing teams to deliver value incrementally while addressing risks early. This approach fosters adaptability, innovation, and stakeholder engagement, making it particularly effective in dynamic industries experiencing rapid technological advancements (Cohen et al, 2004).

The Waterfall method is a linear and sequential project management approach that follows distinct phases, such as initiation, planning, execution, and closure. Each phase must be completed before the next beginning, ensuring a structured workflow but limiting flexibility in responding to changes. Each stage in Waterfall — from requirements gathering and design to implementation and testing — must be completed before moving on to the next (Dursun et al., 2023). The method emphasizes a clear documentation process, which aids in managing timelines, resource allocation, and scope. However, its rigidity can present challenges in dynamic environments where requirements may change, as revisiting completed stages is often costly and time-consuming (Thesing et al., 2021). Despite this, the Waterfall Method is widely favored for projects requiring high levels of planning, where flexibility is secondary to stability and predictability (Serpell and Rubio, 2023)

2.5. Project Management in Data Center

Project management in data centers presents unique challenges and considerations due to the complexity, scale, and critical nature of these facilities (Wiboonrat, 2018). Effective data center management requires careful attention to resource planning, risk assessment, and stakeholder communication, given the high stakes of downtime or failures (Liu et al., 2011). Traditional project management techniques, such as structured phases for planning, execution, and monitoring, are often combined with adaptive approaches to accommodate the rapid technological advancements and shifting client needs typical in this environment. Specialized methodologies, like agile frameworks, are frequently adopted to allow for iterative improvements and flexibility (Balasubramaniam et al., 2023). Additionally, data center project management often involves robust change management processes to address the multifaceted interactions between systems, as well as strong emphasis on compliance with standards and best

practices for operational excellence. By balancing structured and flexible approaches, data center project managers can ensure optimized performance and long-term reliability in these mission-critical facilities (Wiboonrat, & Kaewsiri, 2015)

2.6.Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a mathematical and non-parametric approach used to assess the efficiency of decision-making units (DMUs), which can represent various entities such as companies, projects, or departments. DEA evaluates the relative efficiency by comparing multiple inputs and outputs, allowing for a comprehensive measurement of performance even in cases where inputs and outputs are multidimensional or complex (Cooper et al., 2011). DEA is commonly applied across fields like operations research, economics, and project management. It helps organizations identify best practices, allocate resources, and improve processes by highlighting inefficiencies in comparison to an "efficient frontier," which is defined by the most efficient DMUs (Ji & Lee, 2010). In the data center industry, DEA can be used to assess resource utilization, energy efficiency, and workload distribution, optimizing data center operations to meet the evolving demands of cloud computing, artificial intelligence, and big data (Cooper et al., 2011).

3. LITERATURE REVIEW

This literature review aims to provide a comprehensive examination of critical aspects related to the optimization and management of data centers and project management methodologies. It will delve into **Infrastructure and Workload Management in Data Centers**, addressing key components such as data center definitions, design principles, and the integration of AI workloads to enhance operational efficiency. Following this, the review will explore **Project Management Approaches in Data Center Operations**, focusing on various project management methodologies, including traditional frameworks and their application in data center contexts. Additionally, the review will analyze **Data Envelopment Analysis (DEA) Applications in Project Management**, highlighting how DEA serves as a vital tool for evaluating efficiency and performance across project management offices. Through this structured analysis, the literature review seeks to illustrate the interconnectedness of these topics and their implications for improving data center operations and project management effectiveness.

3.1. Infrastructure and Workload Management in Data Center

This section examines the critical components of infrastructure and workload management within data centers, which are essential for achieving optimal performance and operational efficiency. It begins by defining the concept, structure, and significance of data centers within the modern digital ecosystem. The discussion then shifts to data center design, outlining the key principles and considerations that influence effective spatial planning and resource allocation for supporting heterogeneous workloads. Lastly, the section addresses the increasing importance of AI workloads in data centers by analyzing the distinct challenges and technical requirements associated with AI-driven applications. A comprehensive understanding of these components is fundamental to managing data center resources efficiently while aligning with the evolving demands of contemporary computational environments.

3.1.1. Data Center

Yang, et al. (2024) mentioned that load balancing has become increasingly critical in modern data centers due to the growing volume of traffic. Most data centers rely on software-based load balancers, which, while flexible, consume significant server resources and struggle to scale with increasing traffic demands. There is a rising need for Layer-4 load balancers that require more detailed inspection of packet headers, but hardware-based load balancers, although capable of addressing these demands, are much more expensive. Data centers frequently upgrade their infrastructure, resulting in many outdated switches, many of which are still functional and equipped with high-performance memory like Static Random Access Memory (SRAM). This paper introduces the Bit-based Collaborative Load Balancer (BCLB), a novel approach that utilizes these existing switches to enhance load balancing. Unlike traditional methods that distribute rules across multiple load balancers, BCLB enables switches along the data path to collaboratively inspect different bits in packet headers. By dividing the task of checking the entire 296-bit 5-tuple in IPv6 packets, BCLB ensures that rule updates do not disrupt the load balancing process. The problem is formulated as an optimization challenge, and a dynamic programming algorithm is proposed to solve it. Simulations using real-world traffic datasets, and a P4-based prototype demonstrate that BCLB outperforms previous rule-based cooperative load balancing schemes (Yang, et al., 2024).

Huang, et al. (2024) introduce that modern data center switches utilize on-chip shared buffers to absorb traffic bursts and prevent packet loss during transient congestion. However, as the buffer-per-port-per-Gbps capacity decreases in production data centers, managing these buffers efficiently to meet the needs of heterogeneous traffic becomes increasingly challenging. Current shared buffer management policies typically operate in two stages: first, identify short flows arriving at ports, and then allocate additional buffer space to these ports. Unfortunately, the absence of isolation between long and short flows can result in queue buildup and potential packet loss for short flows. To overcome this issue, D2T, a strategy that employs different queue length thresholds for long and short flows. D2T uses a compact data structure to distinguish between flow types and, when both types coexist at the same port, dynamically reduces the threshold for long flows to accommodate bursty short flows.

The implementation of D2T on a P4-programmable switch and perform large-scale simulations. The results show that D2T reduces both the average and tail flow completion times (FCT) for short flows by up to 29% and 62%, respectively, compared to state-of-the-art buffer management policies (Huang, et al., 2024).

Mogal, et al. (2024) in this study aims to evaluate the effectiveness of a hybrid methodology that integrates Long Short-Term Memory (LSTM) and k-Nearest Neighbors (k-NN) models for energy prediction in data centers. The objective is to enhance prediction accuracy and operational efficiency by leveraging the combined strengths of these two machine learning approaches. The proposed LSTM-kNN model demonstrates superior performance compared to individual LSTM and k-NN models, as evidenced by comprehensive evaluations on sample data, achieving a Mean Absolute Error (MAE) of 9.45, Root Mean Square Error (RMSE) of 12.97, and a coefficient of determination (R^2) of 0.89. A comparative analysis underscores the importance of model synergy in improving energy forecasting accuracy. These findings contribute significantly to the development of advanced energy management strategies in data centers, offering crucial insights for stakeholders in optimizing resource allocation, capacity planning, and sustainability efforts. Practical applications include proactive energy optimization measures and cost-effective operational decisions. Future research directions may involve exploring additional machine learning techniques and analyzing the impact of external factors on energy usage patterns. Overall, this study highlights the critical role of machine learning in addressing complex challenges in energy prediction and management within data center environments (Mogal, et al., 2024).

Graf, et al. (2024) presents in this study that modern data centers are experiencing increasing workloads, placing significant pressure on network monitoring solutions that are essential for maintaining correct and efficient operations. While advancements in network programmability have made it easier to collect monitoring data from switches, this has exacerbated bottlenecks in traditional collection-centric approaches, limiting scalability and responsiveness. This challenge becomes more pronounced when multiple monitoring tasks are deployed simultaneously, a common scenario in network management. To address these limitations, this study introduces FARM, a novel and comprehensive selection-centric solution for network monitoring and

management (M&M). FARM simplifies the development and deployment of M&M tasks while ensuring effectiveness and scalability. Its key innovation lies in its holistic design, which adopts a global perspective rather than focusing on individual components of network monitoring. FARM integrates a decentralized software architecture, a custom programming model, and a performance optimization framework. It localizes monitoring actions on switches as much as possible, using centralized components only when necessary. Additionally, FARM optimizes task placement by considering constraints expressed in its programming model and identifying commonalities among tasks. Deployed in a production data center, FARM demonstrates substantial improvements in responsiveness (up to 3427 times faster than recent generic approaches and 4 times faster than specialized solutions), as well as significant reductions in network bandwidth usage (10000 times) and computational effort. Placement optimization also exhibits excellent scalability, supporting up to 10,200 seeds across 1,040 switches (Graf, et al., 2024)

Chen, et al. (2024) in this study introduce that modern data centers increasingly run machine learning (ML) applications with strict Service-Level Objectives (SLOs), such as low inference latency. To meet these demands, data centers typically over-provision the number of servers used for inference and isolate these from servers running ML training, as both processes require extensive use of GPUs. This practice, however, results in low GPU utilization and higher capital expenses. If inference and training jobs could safely share the same GPUs while maintaining SLO guarantees, data centers could optimize GPU usage by dynamically adjusting the number of training jobs based on inference demand, thereby increasing overall GPU utilization and reducing capital costs. This paper introduces GPUColo, a two-tier co-location solution that ensures explicit SLO guarantees for ML inference when co-located with training jobs on the same GPUs. The outer tier leverages GPU spatial sharing to adjust the allocation of active GPU threads between inference and training tasks, ensuring inference latency remains within acceptable limits. Since spatial sharing can introduce significant overheads at fine time intervals, the inner tier uses periodic pauses in training jobs to allocate additional GPU resources to inference tasks when needed for prompt latency control. Hardware testbed experiments demonstrate that GPUColo effectively maintains the desired inference latency while maximizing the throughput of co-located training jobs. Furthermore, large-scale simulations using a 57-day real-world data

center trace involving 6,500 GPUs reveal that GPUcolo enables co-location of inference and training jobs with guaranteed latency, potentially saving 74.9% of GPUs and significantly lowering capital expenses (Chen, et al., 2024).

This paper made by Alharthi, et al. (2024) examines the performance of a two-tier Arrayed Waveguide Grating Router (AWGR)-based Passive Optical Network (PON) data center architecture in comparison to traditional AWGR-based PON architecture. The evaluation focuses on various scenarios involving link failures to assess the resilience of both designs. To optimize traffic routing under different failure conditions, a Mixed Integer Linear Programming (MILP) model is developed, and both power consumption and delay performance are analyzed. The findings reveal that the two-tier AWGR architecture outperforms the traditional AWGR-based design, reducing power consumption and delaying by up to 10% and 61%, respectively (Alharthi, et al., 2024).

3.1.2. Data Center Design

In this study Wittenhagen, et al. (2024) introduce that the future wireline communication systems demand data rates exceeding 224 Gbit/s. This paper presents the design of a 112 Gbaud transmitter and receiver front-end, including a 112 GS/s sampler, implemented in 22FDX technology to meet bandwidth requirements greater than 56 GHz. The transmitter achieves a signal-to-noise-and-distortion ratio (SNDR) of over 39 dB, while the receiver achieves an SNDR of over 37 dB, excluding jitters, with a power consumption of only 191 MW from a 1.4/0.9V supply. The step responses of the circuits are incorporated into a co-packaged optical-link PAM-4 224 Gbit/s simulator, which includes components such as the transmitter, substrate channels (accounting for NEXT/FEXT), driver, optical channels, photodiode, transimpedance amplifier (TIA), and receiver/DSP equalization. This simulation verifies the system's signal-to-noise ratio (SNR) and symbol error rate (SER). The system utilizes a channel with up to 25 dB attenuation at Nyquist, requiring a 32-tap feed-forward equalizer (FFE) and a 1-tap maximum likelihood sequence estimation (MLSE) equalizer to reach the forward error correction (FEC) limit of 103 (Wittenhagen, et al., 2024).

Power management strategies and the impact of carbon dioxide emissions from data centers have garnered considerable global attention. The rapid increase in energy

consumption in data centers has led to significant challenges, including high operational costs, depletion of non-renewable resources like coal and petroleum, and the emission of greenhouse gases such as CO₂, which contribute substantially to climate change. To address these issues, this study models the energy consumption of data centers, offering insights aimed at reducing the global carbon footprint and energy costs. The model prioritizes the use of green energy by phasing out reliance on brown energy sources. An algorithm is developed to calculate the hourly CO₂ emissions produced by various energy resources. Using a support vector regression algorithm, the model accurately projects the energy consumption of data centers powered by green energy. Experimental results consistently demonstrate the model's high prediction accuracy for energy usage, providing a valuable tool for optimizing energy efficiency and sustainability in the development of future data centers (Lu & Li, 2024)

Bhattacharya, et al., 2022 introduce the rapid growth of Internet applications and the corresponding surge in demand for cloud services have introduced significant challenges for data center networks (DCNs). Traditional wired DCNs rely on a multi-layer structure, which often leads to congestion at higher-layer switches. Additionally, the complex cabling in these wired systems obstructs airflow, reducing cooling efficiency and increasing energy consumption. To address issues related to flow congestion, power consumption, and wiring complexity, this paper presents an intra-DCN architecture based on free space optical (FSO) wireless communication. The proposed scheme leverages the spatial positioning of FSO transceivers at varying heights to enable obstruction-free transmission for inter-rack communication. A mathematical model is formulated to optimize the arrangement of transceivers while ensuring the requirement for direct line-of-sight communication between nodes. Performance evaluation through simulation demonstrates that this architecture significantly reduces power consumption while enhancing network performance in terms of flow completion time and server throughput, outperforming traditional wired DCNs (Bhattacharya, et al., 2022)

Wang, et al., 2022 find in this study that memory resources in data centers often suffer from low utilization and a lack of dynamic capabilities. To address this, memory disaggregation decouples CPU and memory, using approaches like RDMA or Compute Express Link (CXL). While RDMA requires code refactoring and introduces

higher latency, CXL supports native memory semantics but is limited to the rack level. Moreover, memory pooling and sharing via CXL is still in early stages of exploration. This paper proposes a "CXL over Ethernet" approach, enabling host processors to access remote memory with native semantics over Ethernet, extending the physical range across servers and racks by integrating CXL and RDMA technologies. A prototype with one server and two FPGA boards connected via a 100 Gbps network demonstrates the effectiveness of this approach, optimizing memory access through data caching and congestion control. This reduces the average latency to 1.97 μs —37% lower than the industry baseline—and down to 415 ns when memory accesses hit the FPGA cache (Wang, et al., 2022)

In this research Zilin, et al., 2022 find that with the continuous development of China's economy, energy consumption is rising, leading to a growing energy shortage. The escalating global energy crisis, coupled with increased awareness of environmental protection and energy conservation, has highlighted the significant environmental impact of large data centers. Consequently, maximizing energy utilization has become paramount, making green energy conservation the primary goal in data center construction, with green data centers emerging as a core concept. This paper constructs a system model for a new green data center and designs a task scheduling strategy to enhance its efficiency. To minimize the extra overhead associated with task migration, a dynamic load forecasting method is employed to predict the data center's load intensity over short periods, allowing for optimal timing in switching loads between servers. Experimental results indicate a high accuracy for this algorithm, with scheduling effectiveness reaching 95.14%. The design and implementation of a highly energy-saving and reliable green data center construction scheme hold practical significance, providing valuable insights for related research (Zilin, et al., 2023)

As the IT infrastructure in the information society, Lu, et al., 2023 finds that data centers are playing an increasingly crucial role in storing and managing vast amounts of key data. Consequently, the industry is paying more attention to achieving intelligent management of data center operations. In this context, the data center within an all-in-one smart energy station is tasked with providing various resources for the power Internet of Things while also handling commercial operations and diversifying profits. This paper proposes a design for a data center in a multi-station intelligent

energy station based on convolutional neural networks. By inputting data into the neural network and setting parameters for training, the state and performance of the equipment can be comprehensively analyzed. The results indicate that, compared to traditional algorithms, the proposed method reduces the number of protection routes, total link length, and resource occupancy rate, thereby effectively enhancing network resource utilization and improving the viability of the data center network. The integration of artificial intelligence and deep learning not only elevates the intelligence level of the data center in the smart energy station but also positively influences its operation and maintenance efficiency. As a result, designs based on intelligent early warning systems have become a focal point of research (Lu, et al., 2023)

Bhattacharya, et al., 2022 discovered that the underwater data center project involves installing Internet facilities, such as servers, in submarine containers with cooling functions, allowing for the sinking of the data center to address various shortcomings of land-based facilities. This paper analyzes the design challenges associated with the shell of an underwater data center by developing a model for the number of servers and applying mathematical-physical methods. An integer programming model is established to determine the maximum number of servers under space constraints, focusing on optimizing server placement. To tackle the heat dissipation issue, the study employs Newton's law of cooling to calculate the total heat dissipation of the container utilizing convection heat transfer methods. By assessing the relationship between heat dissipation and the heat production of individual servers, the research identifies the maximum number of servers that can operate within the temperature limits. Additionally, a fin structure is selected to enhance the contact area between the container and seawater, thereby improving the cooling efficiency of the data center. The integration of the integer programming model with the cooling model results in a server number model, which, through calculations, reveals the maximum number of servers that can function effectively in a cylindrical fin container. The validity of the results is further confirmed through CFD (Computational Fluid Dynamics) calculations. This research offers optimization suggestions for the design of underwater data centers by providing insights for related companies (Wang, et al., 2023)

Wu, et al., 2022 in this study focuses on the three-dimensional intelligent layout of assets within data center spaces of varying sizes, guided by the functional requirements and design standards outlined in GB50174-2017. Equipment is categorized into multiple asset combination variables, with their vertical and horizontal coordinate positions designated as layout variables. A mathematical model is developed to assess the occupied volume, ensuring that the power consumption density, cabinet occupancy ratio, battery room occupancy ratio, power room occupancy ratio, and air conditioning room occupancy ratio meet mutual constraints. The research establishes a multi-objective optimization model by deriving single-objective optimization results for each of these factors, as well as the adjacent distance of areas, net height, required air conditioning cooling capacity, deployment environment limitations, and basic size criteria. To effectively address this, a population-based graph structure description is created, and an improved ant colony algorithm is introduced. This algorithm leverages search direction as the solution space for transfer probability while integrating pheromone volatility based on deployment criteria, facilitating multiple iterations for optimal solutions. By employing lightweight and assisted computing techniques, the study achieves the rapid generation of digital 3D intelligent layout solutions for data centers. Experimental results demonstrate that the proposed method significantly reduces design workload by 95%, generating ten optimal forward design solutions within five minutes and enabling quick exports of 3D design models. This approach greatly enhances the design efficiency of data centers (Wu, et al., 2023)

Wu, et al., 2022 find in this study that in contemporary hyper-scale data centers, carbon emission indicators have become a crucial consideration, reflecting power efficiency. Traditionally, power efficiency focused on components like CPU/GPU performance, thermal design, and fan power, with silicon vendors continuously evolving their products to achieve higher performance per watt. However, from a data center perspective, optimizing the system power supply is equally essential for enhancing power efficiency and reducing carbon emissions, particularly in high-density rack server systems. While the 12V input power supply has been the most common solution in rack design, the associated power loss increases significantly as system power consumption rises. To address this issue, this paper introduces a novel 48V system power supply solution designed specifically for high-density rack configurations. This 48V system can support up to 36 kW of power capacity with dual

power inputs, achieving a 2% efficiency improvement over conventional 12V systems. Furthermore, power loss on the rack bus bar can be reduced by up to 93%, resulting in a 37.5% reduction in the total number of rack power supply units needed. The 48V power supply system is already deployed in Baidu's data center, and the paper also includes a total cost of ownership (TCO) calculation based on volume deployment data, emphasizing its potential for carbon emission reduction (Wu, et al., 2022)

Hsu, et al., 2022 studied in this study that the increasing complexity of PCB design challenges in data center platform design is driven by the proliferation of thousands of signals and higher data rates. To address these challenges, designers must adopt advanced PCB technologies, including lower-loss materials, smaller drill sizes, back drilling, and higher layer counts. Ensuring the quality of these designs and their manufacturing processes is crucial. The Advanced Impedance and Loss Characterization (AIBC) tool has been developed to provide efficient and accurate electrical characterization of PCBs, capturing essential design and manufacturing qualities, such as drilling and etching quality, as well as variations in manufacturing. Through comprehensive in-board impedance and loss measurements, AIBC effectively identifies design defects, facilitating improvements for subsequent PCB re-spins. This early visibility into potential issues is critical for enhancing PCB vendor quality, thereby reducing downstream risks and improving overall product quality, ultimately supporting faster time-to-market for customers (Hsu, et al., 2022)

Putra, et al., 2022 As a maritime nation, Indonesia recognizes the need for a robust marine data management system to enhance its maritime data and information systems. The Indonesian National Oceanography Data Center (InaNODC) is a web-based platform designed to archive, visualize, and share marine environmental and ecosystem data. Several prototypes of InaNODC have been successfully developed, and ongoing evaluations have led to continuous improvements in the system. Currently, InaNODC has reached the final stage of development, focusing on Deployment and Maintenance. This article provides an overview of the current InaNODC and its supporting systems. Unlike its previous monolithic architecture, the updated InaNODC employs microservice architecture, adhering to international marine data standards. The system currently houses over 100 years of marine data, which can be easily downloaded and analyzed. Users are also encouraged to share their

marine data within the system. Before entering the deployment stage, InaNODC underwent several tests to ensure technological readiness and information security. Additionally, various support systems have been developed to facilitate use, management, and maintenance for both users and administrators (Putra, et al., 2022)

Bhattacharya et al. (2023) note that erasure coding has become a widely adopted solution in modern data centers to mitigate frequent failures; however, it is often associated with substantial cross-rack traffic during parity updates. In response to this limitation, the study introduces a rack-coordinated update mechanism aimed at minimizing such traffic. The proposed approach involves two sequential phases: a delta-collecting phase that aggregates data delta chunks, and a selective parity update phase that refreshes the parity chunks based on the observed update pattern and parity layout. The authors further present RackCU, an optimized rack-coordinated update solution designed to reach the theoretical lower bound of cross-rack update traffic. Reliability analysis demonstrates that RackCU reduces the likelihood of data loss by shortening the update duration. Extensive evaluations, conducted through both large-scale simulations and real-world data center testing, indicate that RackCU reduces cross-rack update traffic by 16.5% to 77.1% and enhances update throughput by 24.9% to 77.2% (Gong et al., 2023).

Ming et al. (2023) examine the role of Software-Defined Networking (SDN) in enhancing flexibility and control within data center networks by decoupling control and forwarding functions. The study analyzes the technical characteristics of both modern data center networks and SDN, proposing an application architecture for SDN integration. The evaluation focuses on routing performance requirements from the SDN perspective and presents solutions that address limitations in cloud computing network virtualization. The proposed scheme facilitates a unified approach to computing, storage, and networking, enabling automated resource deployment, real-time resource scheduling, and efficient network diagnostics. Additionally, the framework supports the dynamic incorporation of new services, thereby promoting rapid network innovation. The findings suggest that this SDN-based integration strategy offers a viable solution for cloud computing data center operators aiming to reduce maintenance costs while simultaneously improving overall service delivery and user experience (Ming et al., 2023)

Han, et al., 2024 worked to find that Data centers (DCs) are essential in the contemporary digital landscape, where high service reliability is vital for delivering the expected quality of service. This study presents a model for task execution progress through the lens of process sequence dependency, comprehensively considering the order of all processes involved in completing a task. An innovative process migration mechanism focused on sequence dependency is developed, detailing the features of sequence-free, sequence-strict, and sequence-relied tasks. Additionally, the study addresses single-point and multipoint power supply failures within a district, examining the roles of power supply systems (PSSs), backup power systems, and uninterruptible PSSs in DCs based on varying levels of power supply importance. A data-density-based dispatch model is proposed to tackle issues arising from power supply failures. Lastly, the research introduces a two-stage robust optimization model that accounts for prediction errors in photovoltaic power and the arrival rates of processes in real-world DC operations, utilizing a nested column-constraint generation algorithm for problem-solving. Simulation results demonstrate that the proposed task migration mechanism effectively facilitates economic task reallocation, aligning task completion priorities and sequence dependency requirements (Han, et al., 2024)

Qi et al. (2023) presents a study focused on the design of data center network (DCN) topologies aimed at reducing latency and minimizing the number of links by leveraging deep reinforcement learning (DRL). The proposed framework incorporates both single-objective and multi-objective DRL agents that learn optimal DCN topologies based on predefined node traffic matrices. Within this framework, link matrices are utilized to define states and actions, while the average shortest path length and action penalty serve as components of the reward function. Comparative evaluations against widely adopted DCN topologies demonstrate the superior performance of the learned configurations in terms of reduced network delay. Furthermore, the authors suggest that the framework is adaptable for optimizing alternative metrics, such as throughput, by modifying the reward structure, thereby offering a flexible approach to topology optimization in data center environments (Qi et al., 2023)

Zha et al. (2023) investigate the growing implementation of Software-Defined Networking (SDN) technologies in cloud data centers to enhance connectivity and

communication infrastructure. Despite these advancements, effective network measurement—an essential aspect of daily operations—remains constrained by the limited capabilities of conventional network devices. Addressing the challenge of balancing resource consumption with the need for accurate and timely measurements, the study highlights the emergence of Software Defined Measurement (SDM) as a flexible and programmable solution within SDN environments. A key development in SDM is the utilization of widely deployed Open vSwitches (OVS) for traffic monitoring. However, limited attention has been given to exploring design strategies for implementing traffic measurements within OVS. This research systematically examines various design alternatives, evaluating trade-offs between resource consumption, measurement accuracy, implementation complexity, and switching speed. Experimental results and comparative analyses quantitatively demonstrate these trade-offs and validate the practicality of integrating monitoring capabilities into OVS. The findings provide valuable guidance for selecting appropriate design schemes to fulfill diverse monitoring and performance evaluation requirements in SDN-enabled data centers (Zha, et al., 2023).

3.1.3. AI Workload in Data Center

Hogade & Pasricha, 2022 find that the increasing energy consumption of data centers, driven by the rise of AI workloads, poses significant environmental and operational challenges, particularly in terms of higher carbon emissions and operational costs. To address the need for balancing performance with sustainability, this research introduces a novel approach that integrates Game Theory (GT) with Deep Reinforcement Learning (DRL) for optimizing AI inference workload distribution in geo-distributed data centers. This method aims to reduce both carbon emissions and cloud operating expenses, which include energy and data transfer costs. By embedding non-cooperative Game Theory into the DRL framework, data centers can make more intelligent decisions about workload allocation while accounting for the heterogeneity of hardware resources, fluctuating electricity prices, inter-data center transfer costs, and carbon footprints. Extensive experiments show that the proposed game-theoretic DRL (GT-DRL) approach outperforms traditional DRL-based and other optimization techniques, achieving significant reductions in carbon emissions and operational costs without sacrificing computational performance. This strategy offers a promising

solution for enhancing sustainability and cost-efficiency in data centers managing AI workloads across multiple geographic locations (Hogade & Pasricha, 2022)

Karthikeyan, et al., 2022 introduced in this research that Workload prediction is a crucial factor in cloud data centers for maintaining resource elasticity and scalability. However, achieving high accuracy in workload prediction remains challenging due to issues like redundancy, noise, and inherent low prediction precision. This paper proposes a novel approach called the Tree Hierarchical Deep Convolutional Neural Network (T-CNN), optimized with a Sheep Flock Optimization Algorithm, to enhance workload prediction in sustainable cloud data centers. Initially, historical data from the cloud data center is preprocessed using the kernel correlation method. The T-CNN model is employed for dynamic workload prediction in cloud environments, with its weight parameters optimized through the Sheep Flock Optimization Algorithm. The proposed COSCO2 method effectively predicts upcoming workloads and reduces excessive power consumption in cloud data centers. To evaluate its effectiveness, the model was tested using two benchmark datasets: NASA and Saskatchewan HTTP traces. The simulations, carried out using Java, revealed that the method achieved notable improvements in both accuracy and energy consumption compared to existing approaches. Specifically, it showed up to 32.95% higher accuracy and 36.5% lower energy consumption for the NASA dataset, and up to 29.09% higher accuracy and 33.74% lower energy consumption for the Saskatchewan dataset, outperforming techniques like the Auto-Adaptive Differential Evolution Algorithm, BiPhase Adaptive Learning Neural Network, and other time-series forecasting models for cloud workload prediction (Karthikeyan, et al., 2022)

Lawo, et al., 2024 find in this study that Data centers, cloud, and edge computing platforms are increasingly handling heavy AI-based workloads, leading to two significant concerns: reducing the networking overhead on host processors to allow them to focus solely on AI processing and providing quantum-resilient protection for connections running such workloads. This paper introduces the concept of a "zero-tax data center," which is achieved by offloading networking functions from the host to the network itself. Specifically, it highlights the implementation of post-quantum cryptography algorithms that provide quantum-resilient links. The paper demonstrates how the complex processing of these cryptographic algorithms is transferred from the

host to the network by utilizing data-processing units (DPUs), effectively mitigating the burden on host processors while maintaining high security standards against quantum threats (Lawo, et al., 2024)

3.2. Project Management Approaches in Data Center Operations

This section explores various project management approaches employed in data center operations, emphasizing the significance of structured methodologies in ensuring successful project execution. It begins with an overview of **project management**, outlining fundamental principles and practices that govern project planning, execution, monitoring, and closure. The discussion then focuses on the **Waterfall project management method**, a traditional approach characterized by its linear and sequential phases, commonly applied in data center projects where requirements and timelines are well-defined. Finally, the section examines project management within the context of data centers, highlighting strategies and techniques specifically adapted to address challenges such as resource allocation, risk mitigation, and stakeholder coordination. Understanding these approaches provides a foundation for analyzing how effective project management contributes to enhanced operational efficiency and the achievement of organizational objectives in complex data center environments.

3.2.1. Project Management

Wu et al. (2020) find that the tackles the growing complexity of shipbuilding project management due to industry growth and international collaboration. Traditional manual methods struggle to keep pace, hindering company development. This paper proposes an information technology solution using an SQL Server database. This system organizes data, integrates requirements across the entire project lifecycle, and creates a comprehensive ship product data model. The benefits include timely and accurate data delivery, streamlined project execution, and a shift from disorganized information and chaotic processes to electronic project management, unified data management, and online business process handling. Ultimately, this approach improves efficiency and reduces costs (Wu et al., 2020).

Serpell and Rubio (2023) stress the importance of project management (PM) skills in construction companies for project success. Even though these companies seem like

natural fits for PM due to their project-based work, many projects fail due to weak PM practices. An effective PM requires companies to be organizationally ready, considering cultural, environmental, and internal structures. The study proposes a framework to assess this readiness, but its application to construction and mining companies revealed a surprising lack of preparedness despite acknowledging the importance of PM. This highlights the need for construction companies to improve their internal conditions to effectively adopt strong project management practices (Serpell and Rubio, 2023).

3.2.2. Project Management Waterfall Method

This paper explores the differences, benefits, and constraints between process-driven and agile methods, both of which follow iterative, test-driven approaches. The study addresses the research questions: What distinguishes these approaches from a practitioner's perspective? How can a decision model be established to select the most appropriate approach for a specific project? To answer these, the study develops a decision model for selecting a procedural model for project management, based on Adam's (1996) modeling process. A research gap was identified through a systematic literature review following Vom Brocke et al. (2009), providing a current state-of-research overview. These insights were compared with empirical data gathered from 15 expert interviews across various industries in Germany. The resulting model assists in systematically selecting the appropriate project management approach based on 15 criteria, which fall under the categories of scope, time, cost, organizational context, and project team characteristics. This model not only addresses a significant research gap but also offers practical relevance by incorporating expert interviews, thus enhancing decision support for selecting project management approaches (Thesing, et al., 2021)

This study introduces made by Dursun, et al., 2023 an intuitionistic fuzzy cognitive map (IFCM) to evaluate the importance of performance indicators within the Waterfall project management framework. As the oldest and most linear project management methodology, Waterfall follows a sequential process through several distinct phases. The IFCM approach helps address the inherent uncertainties, vagueness, and hesitation in assessing performance criteria by utilizing intuitionistic decision aid techniques.

The cause-and-effect relationships between these criteria are analyzed to provide a clearer understanding of performance in a Waterfall context. The study includes a case study conducted in a Turkish bank, demonstrating the practical application of the IFCM in evaluating Waterfall project management performance within the banking sector (Dursun, et al., 2023).

Negrete, et al., 2023 find in this research that Project Management (PM) involves the use of specific knowledge, skills, tools, and techniques to manage, control, and track projects, delivering value to customers. Managers with limited PM experience often face challenges when managing high-value projects due to the pressures involved. In today's project-centric work environments, projects come with inherent risks, such as cost overruns and potential cancellations. Failing to deliver projects on time and within budget can have serious repercussions for both the organization and the manager. To address these challenges, PM training must extend beyond just learning PM tools and emphasize understanding the broader impact of managerial decisions. This paper applies State-of-the-Art Matrix (SAM) analysis alongside the PRISMA-P protocol to analyze trends in simulation-based training approaches for project managers and to identify potential areas for future research (Negrete, et al., 2023)

Serpell and Rubio (2023) stress that the Project Management Office (PMO) has recently become a key driver of change and innovation within organizations, significantly influencing project management success and helping achieve organizational goals. However, in many banking organizations, PMOs primarily handle waterfall projects and lack the foundation to adopt agile practices. Transforming a waterfall-based PMO (WPMO) into an agile PMO (APMO) presents unique challenges, particularly in organizations with non-projectized structures. This paper analyzes a real case study of an IT organization to identify the challenges facing WPMOs and introduces the Scalable Agile Transforming Process (SATP) as a flexible framework for guiding this transformation. A key aspect of this transformation is the introduction of a "change coach" role, responsible for training and supporting employees throughout the process. The study's findings emphasize the importance of having a structured, clear approach to transition from WPMO to APMO, offering valuable insights for IT enterprises undergoing similar changes (Hamad & Al Fayoumi, 2018)

3.2.3. Project Management in Data Center

Wiboonrat (2016) argues that traditional project management struggles with the dynamic nature of data centers. The paper proposes Scrum, a flexible agile methodology, as a better fit. Scrum's focus on iterative development, teamwork, and adaptation makes it ideal for managing complex and ever-changing data center projects. By adopting Scrum in Data Center Project Management (DCPM), teams can effectively handle the inherent complexities and uncertainties, leading to a more responsive, efficient process. This agile approach bridges the gap left by traditional methods, aligning with modern data center needs and ultimately improving project success (Wiboonrat, 2016).

Wiboonrat (2016) worked on improving data center project management (DCPM) due to the inherent complexities caused by the sheer number of systems involved (at least 16). Their approach focused on integrating two standards: ISO 26702 (Systems Engineering) and IEEE 1490 (PMBOK). ISO 26702 tackles requirement breakdown using a System Breakdown Structure (SBS), while PMBOK offers project management frameworks for core aspects like scope, time, cost, and quality. This integration, achieved through modeling, prototyping, and development strategies, is investigated alongside stakeholder participation and the optimal sequence for the System Engineering Process (SEP) throughout the data center lifecycle. By effectively controlling technical efforts, this combined approach offers a solution for managing the complexities of DCPM and ultimately improving project success rates (Wiboonrat, 2016).

Wiboonrat & Kaewsiri, (2015) Studied in the context of data center project management (DCPM), this paper examines the importance of effective engineering change management. It proposes a novel engineering change process to enhance governance throughout the entire DCPM lifecycle. Traditionally, design freeze is used to solidify plans and minimize uncertainties. This new process builds upon design freeze but takes it a step further. It incorporates procedures for handling design problems alongside methods to tackle uncertainties, both internal and external. The key advantage lies in structuring the entire data center design process around pre-defined freeze stages. This enables effective governance of engineering changes from

project initiation all the way through to renovation phases (Wiboonrat & Kaewsiri, 2015).

Wiboonrat (2018) Focuses on the complex knowledge and that needs of data center project management (DCPM), this paper highlights the limitations of traditional project and knowledge management approaches. It emphasizes the necessity of synergizing explicit knowledge (best practices, regulations) with implicit knowledge (personal experience, certifications) across 16 different data center systems. The proposed solution is a "data center project phases" (DCPP) framework, visualized as a cyclical process where these knowledge types constantly interact. This framework, explored through qualitative research on 10 data center projects, aims to address challenges faced by knowledge workers and teams throughout the entire DCPM lifecycle, incorporating concepts like postmortem analysis and bounded rationality (Wiboonrat, 2018).

(Chernov, et al., 2023) in this study presents the prevent clashes during IT project team formation, researchers propose a method based on bimatrix game theory, which analyzes interactions between two decision-makers. This approach treats team members with differing visions as players in a game, aiming for a mutually beneficial outcome that strengthens the team. While the method assumes no direct benefit from copying past proposals, it leverages past experiences to identify even better solutions. Although real-world conflicts may be more nuanced, bimatrix game theory offers a valuable framework for analyzing potential clashes during team formation (Chernov, et al., 2023).

Song & Zhou, (2009) in this research paper talked about how important data quality is for sharing agricultural science information. The authors focus on China's "Agricultural Scientific Data Sharing Center" project and discuss how it managed the information quality. The paper covered aspects like setting standards, training staff, and making sure data from different sources fit together. The paper also suggests ways to improve information quality sharing in the future, like better national coordination and stronger rules. Overall, the focus is on making sure agricultural science data is accurate and useful for research (Song & Zhou, 2009).

3.3. Data Envelopment Analysis Applications in Project Management

This section explores the applications of Data Envelopment Analysis (DEA) in project management, highlighting its effectiveness as a tool for evaluating and improving project efficiency. It begins with an introduction to Data Envelopment Analysis, explaining its fundamental concepts, including the assessment of multiple inputs and outputs to determine relative efficiency among decision-making units. The discussion then transitions to the use of Data Envelopment Analysis in Project Management, illustrating how DEA can be employed to optimize resource allocation, performance measurement, and overall project effectiveness. Finally, the section examines the role of Data Envelopment Analysis in Project Management Office, detailing how DEA can support strategic decision-making, enhance project evaluation processes, and facilitate continuous improvement within the project management framework. Through this examination, it helps to provide a better understanding of how DEA contributes to enhancing efficiency and effectiveness in project management practices.

3.3.1. Data Envelopment Analysis

Ji, Y. B., & Lee, C. (2010) introduce a user-written Data Envelopment Analysis (DEA) command for Stata, designed to evaluate the efficiency and productivity of decision-making units (DMUs) through linear programming. Over the years, DEA has become a widely recognized managerial tool for assessing organizational performance, with applications across various sectors, including banking, airlines, healthcare, education, defense, and manufacturing. The **dea** command in Stata streamlines both standard optimization processes and advanced managerial analyses by allowing users to select relevant variables from a Stata dataset and build a customized linear programming model based on specified DEA options. Practical examples provided illustrate how this tool can effectively measure the efficiency of decision-making units (Ji, Y. B., & Lee, C. ,2010)

Aiming to improve how Data Envelopment Analysis (DEA) measures bank efficiency under uncertain conditions, Amirteimoori et al. (2024) introduce a novel DEA-based Malmquist index model. This model surpasses traditional methods by considering both a bank's operating environment and random fluctuations in inputs and outputs. The researchers utilize a two-stage double bootstrap DEA procedure. The first stage

estimates individual banks' technical efficiency using the classic DEA model. The second stage employs a double bootstrap DEA model to assess how contextual factors, such as the number of branches or non-performing loan ratio, influence efficiency. A similar two-stage process is applied to measure productivity change, with researchers estimating stochastic technical efficiency and analyzing how various factors affect relative bank performance. Data from 15 Iranian banks between 2014 and 2021 reveals that factors like the non-performing loan ratio and the number of branches negatively impact both efficiency and productivity change. This emphasizes the importance of optimizing these areas for improved bank performance (Amirteimoori, et al., 2024).

Iranian policymakers face challenges monitoring imports, business practices, and exchange rates due to government support programs for traders (Fesanghari et al., 2024). To address this, researchers propose a novel strategy using Data Envelopment Analysis (DEA) to assess trader actions based on background information. This approach utilizes a specific output-oriented DEA model (SBM-DEA) that analyzes real-world data alongside trader background. Initially considering a wider range of indicators (30 input and 6 output), the model refines them to a core set of 5 and 4 through correlation analysis. The DEA model then measures and rates trader efficiency, with top performers receiving government support. The study validates the model's effectiveness by comparing trader rankings with another method (Best Worst Method) and by identifying "reference traders" with expected strong performance based on market knowledge. This not only reduces risk for others but also allows for performance-based classification of traders, ultimately aiding policymakers in resource allocation and trade policy development (Fesanghari, et al., 2024).

This study (Sakr et al., 2024) tackles a gap in development aid research: how efficiently are funds being used? While the impact of aid is well known, its efficiency remains unclear. The researchers use Data Envelopment Analysis (DEA) to examine how effective development assistance was used to achieve three specific Sustainable Development Goals (SDGs) between 2002 and 2020. Their findings reveal that development assistance often falls short in efficiency, particularly in low-income countries. This suggests a need for better management practices, as improvements could potentially boost efficiency to over 80%. The study also explores the theoretical link between aid effectiveness and a country's governance. Importantly, emphasize

that simply increasing aid levels may not be enough to bridge the financial gap needed to meet the SDGs by 2030 (Sakr, et al., 2024).

Aiming to improve financial sustainability in broiler chicken production, Marmelstein et al. (2024) propose a novel efficiency metric that combines traditional production efficiency with unit cost. This comprehensive approach maximizes return on investment for producers. Researchers employed Data Envelopment Analysis (DEA) to evaluate 31 broiler farms, considering factors like housing, slaughter age, feed consumption, mortality, unit cost, and total broiler weight. The analysis identified the most efficient farms and established benchmarks for best practices. This study underscores the critical role of unit cost in achieving financial sustainability within the agricultural sector. By offering valuable insights and benchmarks for improvement, the research empowers less efficient farms to adopt better practices, ultimately contributing to a more efficient and sustainable poultry industry (Marmelstein, et al., 2024).

Focusing on a previously neglected aspect of Brazilian higher education evaluation, Torres and Ramos (2024) propose a national evaluation model for graduate programs. Existing evaluations often overlook graduate programs, concentrating on undergraduate studies or combined teaching/research. This novel two-stage model considers graduate education as a system with formative activities and scientific production stages. The researchers introduced a centralized two-stage dynamic network data envelopment analysis (DNDEA) model with shared resources, allowing for efficiency decomposition and a more comprehensive assessment of program performance. The model effectively ranks universities and identifies areas for improvement, particularly in scientific production. Interestingly, the study finds a negative impact of COVID-19 on formative process efficiency but no significant regional performance discrepancies. Overall, this research offers valuable insights for improving efficiency and performance in Brazilian graduate programs, contributing significantly to the field of higher education evaluation (Torres and Ramos, 2024).

This study which was made by Pascoe, 2024 examines a common tool for evaluating management choices - Data Envelopment Analysis (DEA). While DEA is powerful, its impact on ranking options with multiple criteria isn't fully understood. This research explores how ignoring a structured approach to these criteria, especially when dealing

with varying objectives, can affect the ranking of options. Also analyze how different calculation methods within DEA impact ranking, with and without a structured approach. Using both simulated and real-world data, the study highlights the benefits of structuring the criteria and the effectiveness of specific DEA methods in differentiating between options with multiple goals and measures. This offers valuable insights for using DEA in complex decision-making scenarios (Pascoe, 2024).

This study expands on Arbabi et al. (2023) by introducing a new method for analyzing efficiency in decision-making units like hospitals. Traditional Data Envelopment Analysis (DEA) compares efficiency, but this research adds "Inverse DEA" (IDEA) to the mix. The IDEA explores how changing inputs or outputs can impact efficiency, providing valuable insights for managers. The model considers both controllable factors (like resource allocation) and uncontrollable factors, allowing for a more nuanced understanding of efficiency. The research demonstrates the effectiveness of this new approach using real-world hospital data (Arbabi, et al., 2023).

The findings of this research are consistent with those of Omir et al., (2024) analyzes the efficiency of Kazakhstan's healthcare system between 2014 and 2021. By using data analysis to track efficiency changes over time. Interestingly, the initial introduction of digital technologies caused a short-term dip in efficiency, but this was followed by long-term improvement. Even the COVID-19 pandemic couldn't significantly reduce the overall efficiency of the healthcare sector in Kazakhstan (Omir, et al., 2024).

3.3.2. Data Envelopment Analysis in Project Management

This study builds on Shirouyehzad et al. (2015) by examining the "agile gap" in project management. Agile approaches aim for continuous software delivery and adaptation to changing environments. The research focuses on construction projects (a dynamic environment) and the importance of understanding the gap between current practices and the desired agile state. Since a clear definition of the desired state might be missing, the study uses Data Envelopment Analysis (DEA) to analyze the perceptions and expectations of both contractors and employers. A case study reveals those areas like "team capabilities," "client involvement," "delivery strategy," and "organizational environment" are critical for closing the agile gap in construction projects (Shirouyehzad, et al., 2015).

Kuchta (2023) tackles a challenge in selecting the optimal project implementation plan within sustainable project management. Traditional methods struggle to balance sustainability across the project lifecycle, especially considering conflicting stakeholder priorities for various sustainability aspects. To address this, Kuchta proposes a novel method using network Data Envelopment Analysis (DEA). This unique approach doesn't require pre-defined weights for individual variables, allowing for the first time a comprehensive and unbiased selection of project variants that consider sustainability throughout the entire project and product lifecycle. This innovative method is particularly valuable for organizations implementing sustainable project management, as it offers a balanced decision-making tool in the face of diverse stakeholder viewpoints (Kuchta, 2023).

Aiming to improve how organizations evaluate lean management projects, Stichhauerova & Pelloneova (2019) propose a novel Data Envelopment Analysis (DEA) approach. Lean methods are popular for boosting efficiency, but robust evaluation methods are needed to assess their success. This DEA approach, a non-parametric linear programming method for comparing decision-making units, analyzes lean project efficiency by identifying key inputs and outputs. By working with planned indicator values, the model helps pinpoint projects with the greatest potential benefit to the organization. Additionally, comparing actual indicator values after project implementation allows the model to determine a project's success relative to similar initiatives. This systematic and quantitative approach offers a valuable tool for evaluating both the efficiency and effectiveness of lean management projects, ultimately contributing to research on operational performance improvement (Stichhauerova & Pelloneova, 2019).

This study aligns with previous research (Trindade et al., 2015) and focuses on evaluating project management efficiency within a Portuguese electricity distribution company. It introduces a model aimed at assessing the efficiency of twenty-five Operational Areas involved in remote-controlled projects for the distribution network. By employing Data Envelopment Analysis (DEA), the study identifies inefficient areas, recommends resource optimization, and highlights best practices for benchmarking. Ultimately, it contributes to literature by offering a quantitative

approach to improve project management efficiency in utility companies, emphasizing the practical use of DEA for operational enhancement (Trindade, et al., 2015)

This study builds on the work of Ahbab et al. (2019), which highlights the common occurrences of cost and time deviations in national road projects, indicating challenges in project management. The effective control of these deviations is paramount for project success, yet there remains limited research on evaluating cost and time management efficiency in civil engineering projects. To fill this gap, the study treats large road projects with poor cost and time management as Decision Making Units (DMUs) in Data Envelopment Analysis (DEA). DEA is utilized to assess relative managerial performance and identify efficient DMUs. Additionally, critical factors impacting both time and cost management efficiency in road projects are identified, including additional work, inaccurate initial project scope, scope changes, and design alterations (Ahhbab, et al., 2019)

Recognizing the limitations of traditional financial metrics in performance evaluation, Maghsoudi et al. (2014) propose a novel approach for project-based organizations, particularly in construction. Their method integrates agile project management principles with Data Envelopment Analysis (DEA) to assess performance beyond just financial data. Agile's adaptability and focus on customer satisfaction are seen as critical for competitiveness, especially in organizations needing to respond swiftly to market changes. The researchers applied their model to six Isfahan construction firms (2011-2014 projects) and found that prioritizing agile practices and their key metrics leads to higher efficiency for project-based organizations (Maghsoudi, et al. 2014)

Oroujia (2017) reviews how Data Envelopment Analysis (DEA) is being used to measure the relative efficiency of project management units. DEA is a common technique that compares units using various inputs and outputs. This review explores how DEA is applied in different project contexts, including enterprise resource planning, research and development, and construction (Oroujia, 2017).

3.3.3. Data Envelopment Analysis in Project Management Office

Building on Coelho et al. (2023), this study investigates the effectiveness of Project Management Offices (PMOs) in managing project portfolios. Researchers examined a Brazilian petrochemical company, using a unique model that considers both cost and

time to measure project efficiency across different complexity levels. The findings reveal an average efficiency range of 40-80%, with improvement observed in two project categories over time, suggesting successful prioritization by the PMO. Interestingly, meeting deadlines emerged as the key factor influencing efficiency. This highlights the importance of time control for the company. The research suggests further investigation into management techniques specifically targeting on-time project completion (Coelho et al., 2023).

This study following Bettin et al., (2010) examines how an IT research institute improved efficiency during an economic downturn. Facing financial strain, the institute implemented a Project Management Office (PMO) to enforce stricter adherence to ISO 9001:2000 standards, particularly within the hardware department. Researchers tracked project compliance data for two years to assess the PMO's impact on hardware department outcomes. In essence, the study investigated whether a more standardized approach to project management, facilitated by the PMO, led to improved results in the hardware department (Bettin et al., 2010).

This study extends the work of Sharifighazvini et al. (2018) by focusing on Project Portfolio Management (PPM), a critical model for assessing, prioritizing, and monitoring projects within organizations. It emphasizes the importance of thorough analysis, alignment with organizational goals, and comprehensive evaluation of costs, benefits, and risks when selecting an optimal project portfolio. Integrating both qualitative and quantitative approaches, this study introduces innovative techniques such as Data Envelopment Analysis (DEA), Fuzzy Analytic Network Process (FANP), and Multi-Objective Non-Linear Programming (MONLP). The MONLP model, solved using an efficient branch and bound algorithm, aids in optimizing project portfolios by considering proximity to risk events and the ability to control and modify them. Applied to a real case study at Mobarakeh Steel Co., this approach demonstrates practical effectiveness in project portfolio management (Sharifighazvini, et al., 2018).

Based on the literature the reviewed the studies offer substantial advancements in data center optimization, AI integration, project management methodologies, and the use of Data Envelopment Analysis (DEA) for efficiency evaluation, yet significant gaps remain unaddressed. Research on data center operations, such as the works of Yang et al. (2024) and Graf et al. (2024), highlights technical improvements like load balancing

and network monitoring, while Chen et al. (2024) and Lawo et al. (2024) explore AI workload management and sustainability. DEA has also been extensively utilized, as shown by Ji & Lee (2010) and Kuchta (2023), for assessing efficiency in sectors ranging from banking to construction. However, these studies often focus on isolated aspects, failing to address the intersection of AI workload integration, project management methodologies, and DEA within the context of data centers. This thesis aims to bridge this gap by integrating AI workload optimization with structured project management frameworks and employing DEA to evaluate both operational and project-level efficiencies. A key differentiator of this study is its comprehensive approach, which examines AI integration from both quality and financial perspectives, assessing not only its impact on operational parameters like energy usage and workload management but also on cost-effectiveness, resource allocation, and risk mitigation. By incorporating tangible outcomes, such as energy efficiency and cost savings, alongside intangible aspects, including project timelines and stakeholder satisfaction, this research provides a holistic evaluation framework. Furthermore, this study introduces a novel perspective by examining the synergy between AI-driven innovations, project management methodologies like Waterfall, and DEA's efficiency measurement capabilities, thereby setting a new benchmark for optimizing the design and operation of AI-integrated data centers. Through this approach, the thesis not only addresses existing research gaps but also contributes valuable insights into the broader implications of AI integration in critical infrastructure.

4. METHODOLOGY

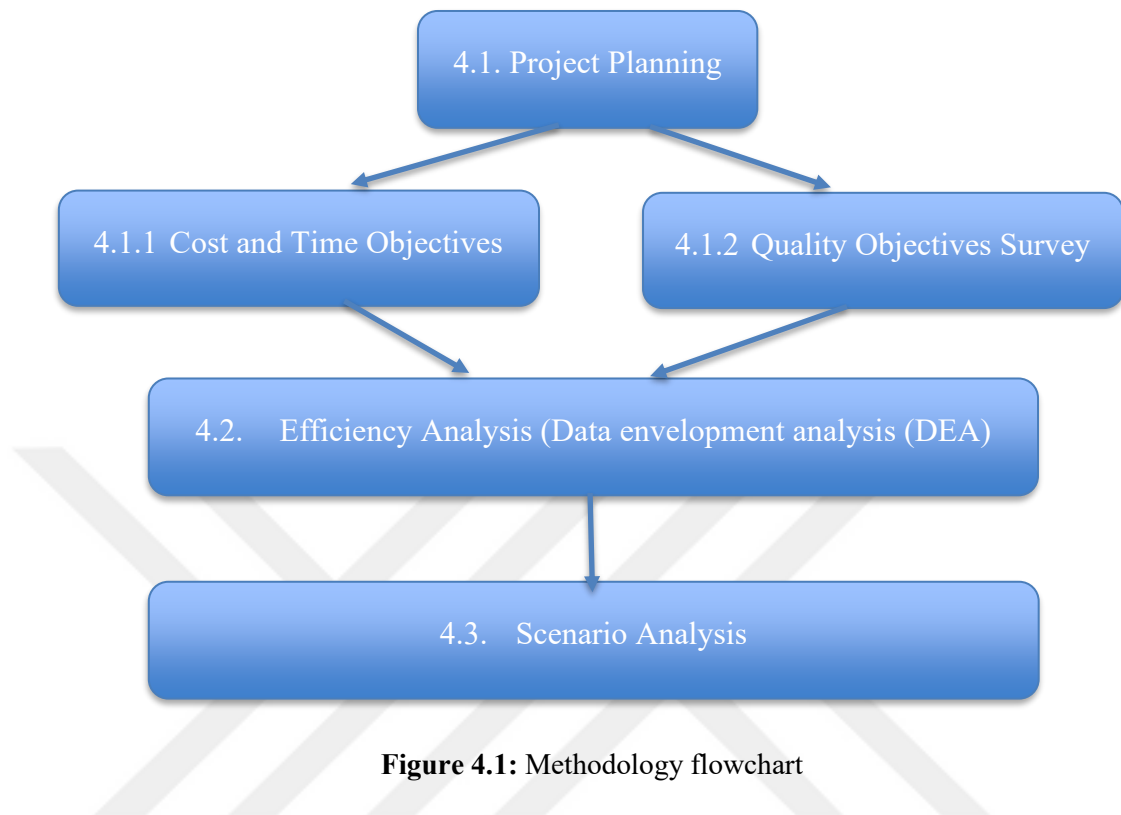


Figure 4.1: Methodology flowchart

4.1. Project Planning

Project planning for data center construction requires a methodical approach due to the complexity and scale of the project. Effective planning must consider the alignment of project goals with the available resources, timelines, and stakeholder expectations. Data center construction often involves managing multiple interdependent activities, requiring a clear definition of project phases, deliverables, and milestones. Additionally, risk assessment and mitigation play a critical role in addressing potential delays or unforeseen challenges. Coordination among diverse teams, including designers, contractors, and engineers, is essential to ensure smooth execution. By using MS Project, the key characteristics of project planning in this context are summarized in figure 4.2 below.

Task Mode	Task Name
	▸ Data Center Building Design Schedule - Option 2 - AI 20-30%
	▸ 1 Planning
	▸ 2 Site Selection & Acquisition
	▸ 3 Design
	▸ 4 Site Preparation
	▸ 5 Construction
	▸ 6 Interior & IT Systems
	▸ 7 Testing
	▸ 8 Commissioning
	▸ 9 Turnover-to-Operations
	10 Project Closure - Sign off

Figure 4.2: Key characteristics of project planning in ms project

4.1.1. Cost and Time Objectives

By using MS Project, cost and time objectives associated with data center projects can be systematically evaluated. The software facilitates the development of comprehensive project schedules, enabling precise tracking of task durations and efficient management of resource allocation through its advanced Gantt chart and reporting functionalities. MS Project's cost analysis tools support the estimation and monitoring of overall project expenses. By simulating various scenarios, the tool provides valuable insights into the trade-offs between cost and time, contributing to the optimization of these objectives and ensuring the effective delivery of project outcomes. In the figures 4.3 presents the MS project for the cost and time objectives.

Mode	Task Name	Duration	Start	Finish	Cost	Predecessors
	▸ Data Center Building Design Schedule - Option 2 - AI 20-30%	117 wks	Tue 7/1/25	Fri 9/24/27	\$13,107,700.00	
	▸ 1 Planning	12 wks	Tue 7/1/25	Mon 9/22/25	\$108,000.00	
	▸ 2 Site Selection & Acquisition	6 wks	Tue 9/23/25	Fri 10/31/25	\$208,500.00	
	▸ 3 Design	18 wks	Mon 11/3/25	Fri 3/6/26	\$350,500.00	
	▸ 4 Site Preparation	16 wks	Mon 3/9/26	Fri 6/26/26	\$164,000.00	
	▸ 5 Construction	56 wks	Mon 6/29/26	Fri 7/23/27	\$1,803,200.00	
	▸ 6 Interior & IT Systems	8 wks	Mon 5/31/27	Fri 7/23/27	\$9,044,000.00	
	▸ 7 Testing	4 wks	Mon 6/28/27	Fri 7/23/27	\$52,000.00	
	▸ 8 Commissioning	4 wks	Mon 6/28/27	Fri 7/23/27	\$114,500.00	
	▸ 9 Turnover-to-Operations	8 wks	Mon 7/26/27	Fri 9/17/27	\$1,260,000.00	
	10 Project Closure - Sign off	1 wk	Mon 9/20/27	Fri 9/24/27	\$3,000.00	64

Figure 4.3: Project cost and time in MS project

4.1.2. Survey Design for Quality Objectives

To effectively evaluate data center quality, the process begins with identifying key quality factors. This is followed by designing a detailed survey aimed at achieving three primary objectives:

- **Defining the Critical Quality Factors for Evaluation.**

The evaluation of a data center's quality requires a structured approach that begins with identifying the key factors that influence its performance, reliability, and efficiency. These quality factors serve as the foundation for assessing the overall effectiveness of a data center in meeting operational, security, and sustainability standards. The selection of these factors is guided by industry's best practices, international standards (e.g., Uptime Institute's Tier Classification, ISO 27001 for security, and Power Usage Effectiveness [PUE] for efficiency), and the specific needs of organizations relying on data center services. The key areas of consideration include infrastructure reliability, energy efficiency, scalability, security, compliance, operational efficiency, and AI workload optimization. Each factor is chosen based on its impact on data center performance and its alignment with emerging technological advancements. By defining these quality factors, the evaluation process ensures a comprehensive assessment that reflects real-world operational challenges and requirements. This systematic approach not only facilitates benchmarking across different data centers but also provides actionable insights for improvements, ultimately enhancing service reliability, cost-effectiveness, and sustainability. Presenting the factors as presented below:

1. **Tier Certifications** – Compliance with Uptime Institute's Tier I-IV classification, indicating the level of redundancy and fault tolerance.
2. **Reliability and Uptime** – The facility's ability to maintain continuous operations with minimal downtime, typically measured as uptime percentage (e.g., 99.99%).
3. **Security and Compliance** – Adherence to global and regional regulations (ISO 27001, PCI DSS) and implementation of robust physical and cybersecurity measures.
4. **Infrastructure and Facilities** – The quality of the building, cooling systems, fire suppression, and overall structural resilience.
5. **Power Usage Effectiveness (PUE)** – A measure of energy efficiency, calculated as the ratio of total facility power to IT equipment power.
6. **Operational Efficiency** – Optimization of workflows, automation, and monitoring tools to reduce overhead and improve performance.
7. **Scalability and Flexibility** – The ability to expand capacity and adapt to changing workload demands without major disruptions.

8. **Customer Service and Support** – The responsiveness and expertise of technical support teams in addressing client needs and incidents.
 9. **Environmental Impact and Sustainability** – Implementation of green energy solutions, carbon footprint reduction, and eco-friendly cooling technologies.
 10. **AI Workload Optimization** – The facility’s capability to support AI computing, including high-density GPUs, cooling solutions, and network bandwidth.
- **Determining Relative Importance (Weights).**

Ranking the significance of various factors contributing to the quality of data centers. By having the survey which is designed to evaluate the quality of data centers across multiple dimensions, focusing on operations, infrastructure, and security. Its primary objective is to gather expert insights to identify strengths and pinpoint areas for improvement in data center performance. In the figure 4.4 below shows the survey to determine weights. In that the participants are asked to rate the importance of various factors on a scale from 1 to 5, where 5 represents "Strongly Important" and 1 represents "Strongly Not Important." This structured approach ensures the collection of precise and actionable data, providing a comprehensive understanding of key quality indicators in data centers.

The screenshot shows a web-based survey interface. At the top, there are tabs for 'Questions', 'Responses' (with a count of 5), and 'Settings'. The main content area is titled 'Section 1 of 11' and 'First Survey: Weight Data Center Quality Evaluation Survey'. Below the title is a rich text editor with formatting options (Bold, Italic, Underline, Link, Unlink). The 'Purpose:' section states: 'This survey aims to evaluate the quality of data centers across multiple dimensions. Your expert insights will help assess the strengths and areas for improvement in data center operations, infrastructure, and security.' The 'Instructions:' section says: 'Please rate the importunity of each statement from 1 to 5, where:'. A bulleted list defines the scale: 1 = Strongly Important, 2 = Important, 3 = Neutral Important, 4 = Not Important, 5 = Strongly Not Important. At the bottom, there is a 'Name' field with a 'Short-answer text' input area.

Figure 4.4: Survey to determine the weights form

To quantify the relative importance of each quality factor assessed in the survey, a weighting system will be employed based on expert feedback. This process involves aggregating the ratings assigned to each factor, multiplying them by the corresponding number of responses, and then calculating the average score. The resulting value represents the perceived significance of each factor, as determined by subject matter experts. To ensure a standardized and objective evaluation, these weights will be normalized, allowing for a comparative analysis of the factors influencing data center quality. This approach enables data-driven assessment, prioritizing key elements across operations, infrastructure, and security. Microsoft Excel will be utilized for data analysis and weight computation, facilitating a structured and efficient evaluation process. As presented in table 4.1.

Table 4.1: Evaluation sub factors

N	Factor
1	Tier Certifications
1.1	DC must meet or exceed the Tier Certifications requirements. (e.g., Tier I-IV).
1.2	The data center must have the level of redundancy and fault-tolerance align with its Tier Certification.
1.3	The facility must demonstrate compliance with Uptime Institute standards for its Tier level.
1.4	There are must clear plans and processes in place to maintain or upgrade Tier Certification as needed.
2	Reliability and Uptime
2.1	The data center must meet industry standards for up-time (e.g., 99.99% or higher).
2.2	There must be efficient generators in place for backup power and cooling systems.

2.3	The data center must provide a high level of redundancy to minimize service interruptions.
2.4	The downtime must incidents minimal and handled efficiently.
3	Security and Compliance
3.1	The data center must have robust physical security measures (e.g., surveillance, access control).
3.2	The data center must adhere to industry standards and compliance frameworks (e.g., ISO 27001, PCI DSS).
3.3	The cybersecurity protocol must frequently be updated and tested.
3.4	The Staff must receive regular training in data security policies.
4	Infrastructure and Facilities
4.1	The data center must be well-maintained, with modern, reliable infrastructure.
4.2	Cooling systems must have energy-efficient and provide sufficient environmental control.
4.3	Cabling and rack organization must be optimized for accessibility and scalability.
4.4	The data center layout must be supporting the efficient power distribution and load management
5	Power Usage Effectiveness (PUE)
5.1	The data center regularly must track and report its PUE to evaluate energy efficiency.
5.2	The facility's PUE score must meet or exceed industry standards for data centers of similar size and capacity.

5.3	The efforts must be in place to improve PUE over time through enhanced cooling and power management.
5.4	The data center's must be design incorporates best practices to maintain a low PUE, indicating strong energy efficiency.
6	Operational Efficiency
6.1	The data center must use automation and monitoring tools effectively to optimize performance.
6.2	Energy efficiency must be a priority, with regular assessments to reduce power usage.
6.3	Capacity planning must be managed proactively to meet future demand.
6.4	The data center staff must demonstrate high levels of expertise and efficiency
7	Scalability and Flexibility
7.1	The data center must accommodate growth without major disruptions.
7.2	There must be a scalable infrastructure solution to support evolving technological needs.
7.3	The data center must allow for flexible customer solutions (e.g., hybrid cloud, colocation).
7.4	The data center's design must support rapid deployment of new services
8	Customer Service and Support
8.1	The data center must offer reliable, accessible, and timely customer support.
8.2	Communication with clients must be clear, transparent, and proactive.
8.3	The data center regularly must seek feedback from clients to improve services.

8.4	SLAs (Service Level Agreements) must be clear and consistently met.
9	Environmental Impact and Sustainability
9.1	The data center actively must work to reduce its carbon footprint.
9.2	Renewable energy sources must be used whenever possible.
9.3	Waste management practices must align with industry sustainability standards.
9.4	The data center must commit to sustainable growth and resource efficiency.
10	AI Workload Optimization
10.1	The data center must support GPU-based infrastructure and AI-specific hardware effectively.
10.2	Cooling systems must be optimized for the higher thermal demands of AI workloads.
10.3	Network infrastructure must ensure low latency and high bandwidth for AI processing.
10.4	Scalable solutions must be available to meet varying AI computational demands.
10.5	Energy efficiency must be maintained despite AI's intensive power requirements.

- **Assessing Overall Quality**

Facilitate the rating of each project option based on the identified quality factors, enabling a comparative evaluation of the alternatives. The purpose of this survey is to evaluate the quality of data centers across multiple dimensions by gathering expert insights. The goal is to assess strengths and identify areas for improvement in key aspects such as operations, infrastructure, and security. Participants are instructed to rate the significance of each statement on a scale from 1 to 5, based on their experience

with various projects. The evaluation is conducted three times, once for each of the following options: operations, infrastructure, and security. where 5 represents "Strongly Important" and 1 represents "Strongly Not Important". This structured approach ensures a comprehensive and systematic collection of data to support the analysis of quality indicators in data center performance.

Figure 4.5: Second survey: data center quality evaluation form

The quality of each proposed option is systematically measured using the results from the quality survey. This assessment considers the weighted importance of each identified factor, enabling a comprehensive evaluation of the quality levels for each project alternative. The survey results provide essential data for analysis, ensuring that quality considerations are objectively measured and integrated into decision-making. The calculation of these quality levels is performed using Excel, as shown in Figure 6., allowing for precise computation and visualization of the evaluation outcomes in a conclusion table, as in Figure 4.5, which presents the answers to the mentioned questions.

4.2. Efficiency Analysis Using Data Envelopment Analysis (DEA)

DEA is applied in this study to assess the efficiency of data center projects by evaluating the relationship between **Cost** and **Time** (inputs) and the **Quality Level** (output). The objective is to determine the most efficient project and identify areas for improvement in others.

Mathematical Representation of DEA

The efficiency score of a one project is determined using the Charnes-Cooper-Rhodes (CCR) Model:

$$\begin{aligned} \text{Max } \theta &= \frac{Y_i}{X_{1i} + X_{2i}} \\ \text{Subject to:} \\ \sum_{j=1}^n \lambda_j X_{1j} &\leq X_{1i}, \forall j = 1, 2, \dots, n \\ \sum_{j=1}^n \lambda_j X_{2j} &\leq X_{2i}, \forall j = 1, 2, \dots, n \\ \sum_{j=1}^n \lambda_j Y_j &\leq Y_i \\ \lambda_j &\geq 0, \forall j \end{aligned}$$

Where:

- X_{1i} represents **input** (cost) for project i.
- X_{2i} represents **input** (time) for project i.
- Y_i represents **output** (quality level) for project i.
- λ_j are the DEA multipliers that determine the contribution of each DMU in forming the efficiency frontier.
- θ is the efficiency score of the project, where $0 \leq \theta \leq 1$

- A project is efficient if $\theta = 1$ and inefficient if $\theta < 1$. Inefficient project can improve by proportionally reducing inputs to reach the efficiency frontier.

Steps for Applying DEA in This Study

1. Define the DMUs:

- Each data center project is considered a Decision-Making Unit (DMU).

2. Select Inputs and Outputs:

- **Input:** Cost and Time.
- **Output:** Quality Level.

3. Data Collection:

- Gather cost, time, and quality level data for each project.

4. Normalize Data:

- Standardize values to ensure comparability across projects.

Inputs Normalization: $X' = \frac{X_i}{\sqrt{\sum X^2}}$

Output Normalization: $Y' = \frac{Y_i}{\sqrt{\sum Y^2}}$

5. Construct and solve the DEA Model:

- Using an **input-oriented CCR model**, solve the linear programming problem using MS Excel Solver

6. Analyze and Interpret Results:

- Identify efficient and inefficient projects.
- Provide recommendations for inefficient projects to optimize cost and time allocation while maintaining quality.

An **input-oriented DEA model** is utilized, as the goal is to minimize resource consumption (cost and time) while maintaining or enhancing the quality of data center projects.

To solve the DEA model, **MS Excel Solver** will be used to compute efficiency scores by solving the linear programming equations. This approach allows for ease of implementation and interpretation while ensuring accuracy in efficiency calculations. The steps of using Excel solver to solve the DEA are as follows:

1. Defining the parameters in DEA Solver Console sheet as in below figure 4.6

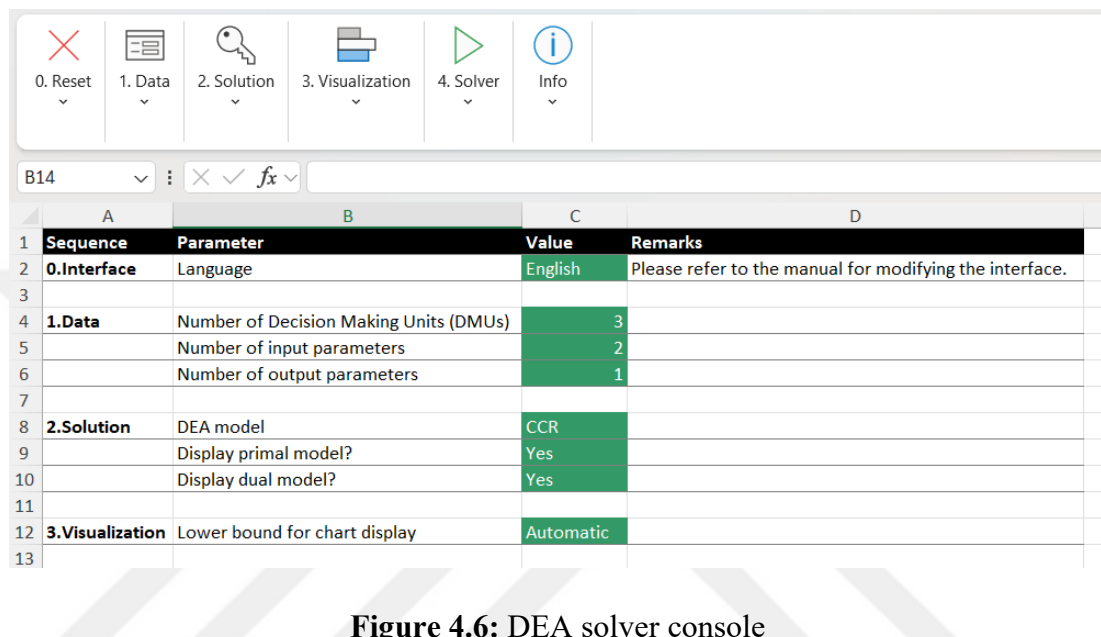


Figure 4.6: DEA solver console

2. Set up the data worksheet and include the inputs and outputs indexes as in below figure 4.7

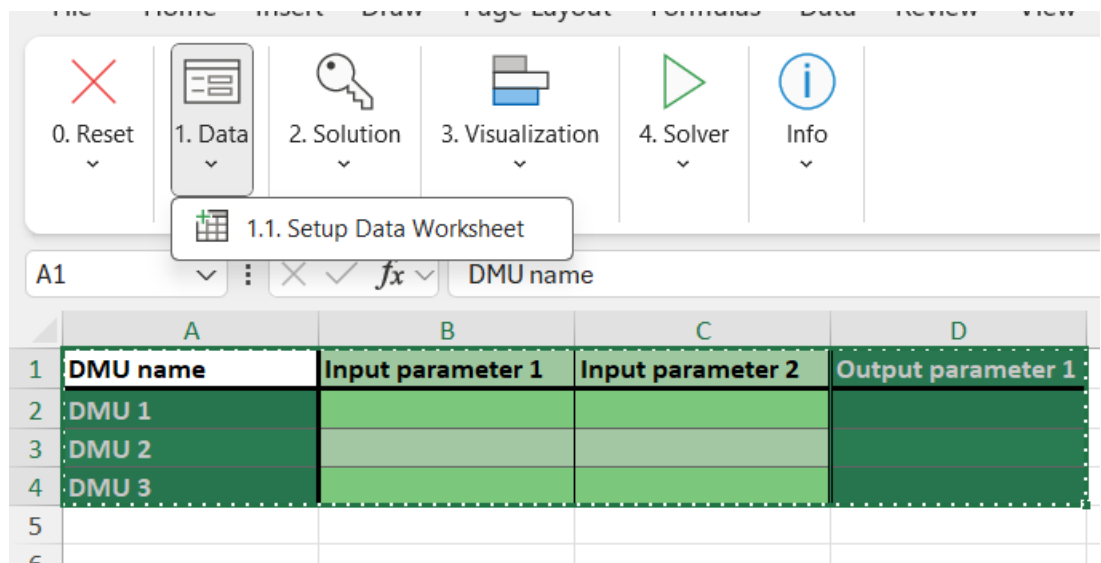


Figure 4.7: Data sheet

3. Setup the solution worksheet which end results present on as in below figure 4.8

4.3.Scenario Analysis

In order to extend the applicability of the DEA model to real-world decision-making contexts, two hypothetical scenarios are developed to evaluate how different operational priorities affect data center efficiency. These scenarios aim to highlight the trade-offs and implications of different planning strategies, helping project managers optimize designs under varied constraints and performance objectives. Each scenario modifies the input–output structure or cost-time assumptions to reflect practical considerations in project planning.

4.3.1. Scenario 1: Discussing Cost Over Time

This scenario explores the impact of planned cost throughout the project lifecycle. The assumption is that by implementing efficiency measures, bulk procurement, or technology optimizations, operational costs are expected to decline incrementally across different project phases. The DEA model is adjusted by modifying the input cost data to reflect decreasing cost values over time while holding other inputs and outputs constant. This scenario aims to simulate how proactive cost management strategies may enhance the perceived efficiency of the data center design without affecting quality or timeline targets.

4.3.2. Scenario 2: Assessing Efficiency with ROI as an Output

In this scenario, Return on Investment (ROI) is introduced as an additional output factor in the DEA framework. While traditional DEA models focus on tangible operational outcomes such as time, cost, and quality, this scenario incorporates a financial performance indicator to reflect business value. ROI is calculated based on estimated returns from AI workload deployment relative to the total project cost. The inclusion of ROI aims to evaluate whether designs that offer stronger financial returns are also considered efficient within the DEA model, providing a more holistic view of project success from both technical and financial standpoints.

5. IMPLEMENTATION AND RESULTS

5.1. Project Planning

In this phase ensures that the project is executed within the defined constraints of cost, time, and quality, aligning with industry standards and stakeholder expectations. The planning process involves setting clear objectives for cost and time, defining quality benchmarks, and establishing a framework for evaluating the overall quality of the project.

5.1.1. Cost and Time Objectives

The cost and time objectives are essential for assessing the feasibility and financial sustainability of different deployment strategies. Given the increasing demand for AI workloads, each option has unique cost implications, mainly due to differences in hardware, cooling systems, power consumption, and networking requirements. In the figures 5.1, 5.2, and 5.3 below the MS Project schedule for each option, which shows the cost and the time of each option.



Figure 5.1: MS project schedule for option 1 – No AI



Figure 5.2: MS project schedule for option 2 –AI 20-30%

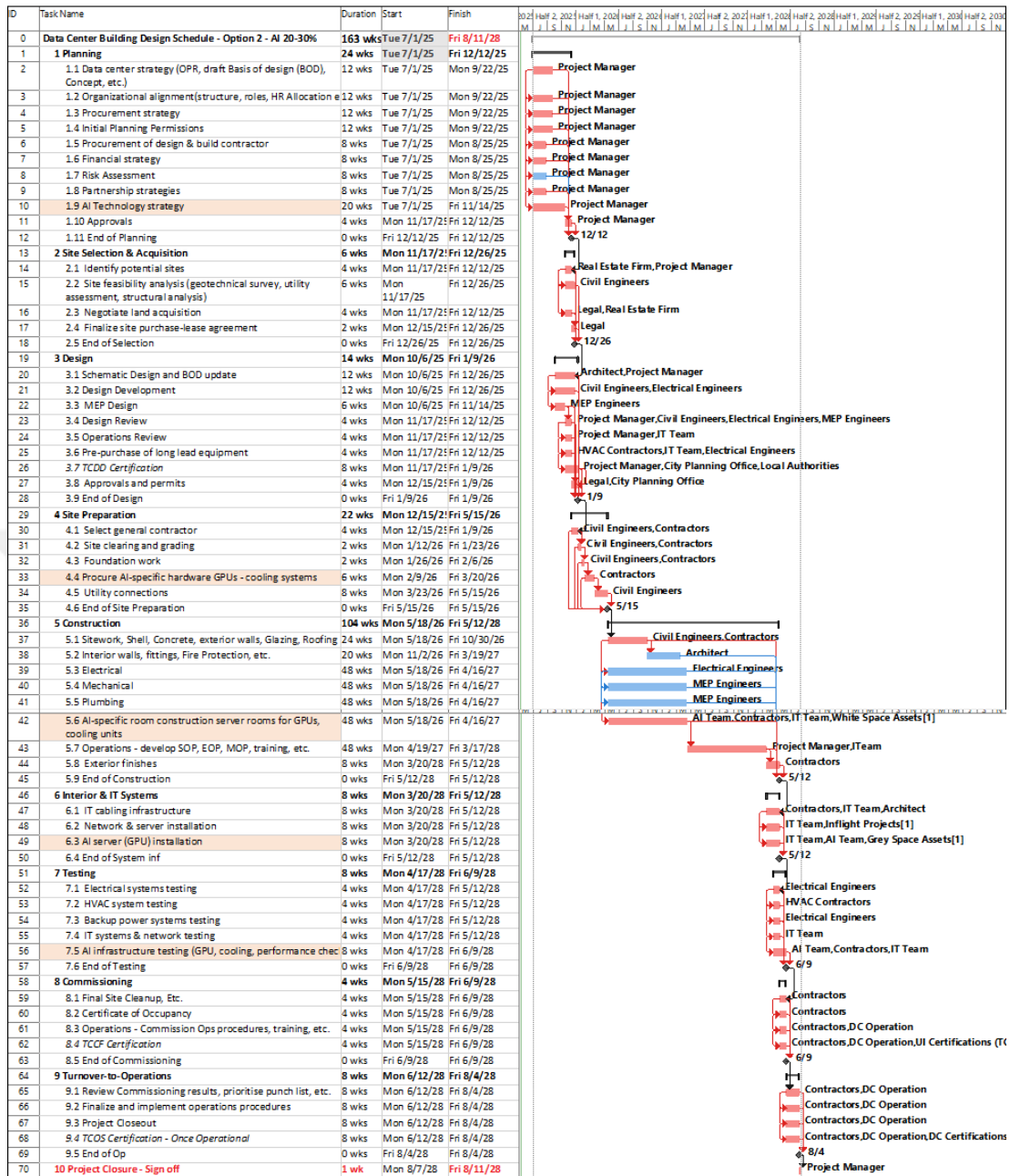


Figure 5.3: MS Project schedule for option 3 –AI 50%

The table below outlines the total project time estimates for each phase, indicating the expected duration for completion. These estimates are based on standard project planning and are structured to reflect the logical sequence of activities. Summarized in the table below 5.1.

Table 5.1: Total project time estimates

Option	Estimated Total Time (Weeks)
Option 1: No AI Workload	117 Weeks
Option 2: 20-30% AI Workload	163 Weeks
Option 3: 50% AI Workload	163 Weeks

In the figures 5.4, 5.5, and 5.6 below the MS Project resource sheet for each option. The total project cost estimates summarized in table 5.2

Resource Name	Type	Material	Initials	Group	Max.	Std. Rate	Ovt. Rate	Cost/Use	Accrue	Base	Code
1					100%	\$0.00/hr	\$0.00/hr	\$75,000.00	Prorated	Standard	
2	Civil Engineers	Work	C		100%	\$11,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
3	Legal	Work	L		100%	\$20,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
4	Architect	Work	A		100%	\$12,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
5	Electrical Engineers	Work	E		100%	\$10,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
6	MEP Engineers	Work	M		100%	\$17,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
7	Procurement	Work	P		100%	\$25,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
8	All Team	Work	A		100%	\$0.00/hr	\$0.00/hr	\$0.00	Prorated	Standard	
9	Contractors	Work	C		100%	\$60,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
10	HVAC Contractors	Work	H		100%	\$17,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
11	IT Team	Work	I		100%	\$40,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
12	Project Manager	Work	P		100%	\$12,000.00/mon	\$0.00/mon	\$0.00	Prorated	Standard	
13	City Planning Office	Work	C		100%	\$20,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
14	Local Authorities	Work	L		100%	\$15,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
15	Planning Team	Work	P		100%	\$24,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
16	Real Estate Firm	Work	R		100%	\$30,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard	
17	White Space Assets	Material	W			\$6,000,000.00		\$0.00	Prorated		
18	Inflight Projects	Material	I			\$2,920,000.00		\$0.00	Prorated		
19	Grey Space Assets	Material	G			\$811,700.00		\$0.00	Prorated		
20	DC Certifications (ISO & CSA & NCA & CST)	Material	D			\$1,140,000.00		\$0.00	Prorated		
21	UI Certifications (TCOS & M&O)	Material	U			\$77,000.00		\$0.00	Prorated		

Figure 5.4: MS project resource sheet of option 1 – No AI

Option 2 - AI 10-20 - Project Professional

File Task Resource Report Project View Help Resource Sheet Format Tell me what you want to do

Team Planner Assign Resources Resource Pool Add Resources Information Notes Details Level Selection Level Resource Level All Leveling Options Clear Leveling Next Overallocation

View Assignments Insert Properties Level

Resource Name	Type	Material	Initials	Group	Max.	Std. Rate	Ovt. Rate	Cost/Use	Accrue	Base
1 Real Estate Firm	Work		R		100%	\$30,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
2 Civil Engineers	Work		C		100%	\$11,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
3 Legal	Work		L		100%	\$20,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
4 Architect	Work		A		100%	\$12,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
5 Electrical Engineers	Work		E		100%	\$10,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
6 MEP Engineers	Work		M		100%	\$10,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
7 Procurement	Work		P		100%	\$25,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
8 Contractors	Work		C		100%	\$60,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
9 HVAC Contractors	Work		H		100%	\$17,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
10 IT Team	Work		I		100%	\$40,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
11 Project Manager	Work		P		100%	\$12,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
12 City Planning Office	Work		C		100%	\$20,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
13 Local Authorities	Work		L		100%	\$15,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
14 AI Team	Work		A		100%	\$60,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard
15 ITeam	Work		I		100%	\$0.00/hr	\$0.00/hr	\$0.00	Prorated	Standard
16 DC Operation	Work		D		100%	\$0.00/hr	\$0.00/hr	\$0.00	Prorated	Standard
17 White Space Assets	Material	W				\$10,620,000.00		\$0.00	Prorated	
18 Inflight Projects	Material	I				\$5,168,400.00		\$0.00	Prorated	
19 Grey Space Assets	Material	G				\$1,436,709.00		\$0.00	Prorated	
20 DC Certifications (ISO & CSA & NCA & CST)	Material	D				\$2,017,800.00		\$0.00	Prorated	
21 UI Certifications (TCOS & M&O)	Material	U				\$136,290.00		\$0.00	Prorated	

Figure 5.5: MS project resource sheet of option 2 –AI 20-30%

Option 3 - AI 50 - Project Professional

File Task Resource Report Project View Help Resource Sheet Format Tell me what you want to do

Team Planner Assign Resources Resource Pool Add Resources Information Notes Details Level Selection Level Resource Level All Leveling Options Clear Leveling Next Overallocation

View Assignments Insert Properties Level

Resource Name	Type	Material	Initials	Group	Max.	Std. Rate	Ovt. Rate	Cost/Use	Accrue	Base	Code	Add New Column
1 Real Estate Firm	Work		R		100%	30,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
2 Civil Engineers	Work		C		100%	11,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
3 Legal	Work		L		100%	20,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
4 Architect	Work		A		100%	12,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
5 Electrical Engineers	Work		E		100%	10,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
6 MEP Engineers	Work		M		100%	10,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
7 Procurement	Work		P		100%	25,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
8 Contractors	Work		C		100%	85,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
9 HVAC Contractors	Work		H		100%	17,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
10 IT Team	Work		I		100%	40,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
11 Project Manager	Work		P		100%	12,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
12 City Planning Office	Work		C		100%	20,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
13 Local Authorities	Work		L		100%	15,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
14 AI Team	Work		A		100%	50,000.00/mon	\$0.00/hr	\$0.00	Prorated	Standard		
15 ITeam	Work		I		100%	\$0.00/hr	\$0.00/hr	\$0.00	Prorated	Standard		
16 DC Operation	Work		D		100%	\$0.00/hr	\$0.00/hr	\$0.00	Prorated	Standard		
17 White Space Assets	Material	W				\$15,600,000.00		\$0.00	Prorated			
18 Inflight Projects	Material	I				\$7,592,000.00		\$0.00	Prorated			
19 Grey Space Assets	Material	G				\$2,110,420.00		\$0.00	Prorated			
20 DC Certifications (ISO & CSA & NCA & CST)	Material	D				\$2,964,000.00		\$0.00	Prorated			

Figure 5.6: MS project resource sheet of option 3 – AI 50%

Table 5.2: Total project cost estimates

Option	Estimated Total Cost (\$)
Option 1: No AI Workload	\$13,107,700
Option 2: 20-30% AI Workload	\$23,109,199.00
Option 3: 50% AI Workload	\$32,705,995.00

5.1.2. Quality Objectives Survey

The quality objectives focus on ensuring that the data center meets industry standards and operates at optimal efficiency. This involves defining key quality factors, determining their relative importance, and evaluating the overall quality through expert surveys.

- **Defining the Critical Quality Factors for Evaluation.**

To assess the data center's quality, it is necessary to establish a set of critical factors that reflect its operational excellence. These factors are:

- **Determining Relative Importance (Weights).**

To quantify the significance of each quality factor, a survey is designed to collect expert opinions. Respondents will rate each factor based on its importance in evaluating data center quality. The collected responses will be analyzed to assign relative weights, ensuring a data-driven assessment.

Survey Results: Importance of Quality Factors in Data Centers

(Scale: 1 = Not Important, 5 = Very Important) in table 5.3 below

Table 5.3: Survey results: importance of quality factors in data centers

Factor	Scores
1. Tier Certifications	
1.1.	4.2
1.2.	5
1.3.	4.8
1.4.	4
2. Reliability and Uptime	
2.1.	4.6
2.2.	5
2.3.	5
2.4.	5
3. Security and Compliance	
3.1.	4.8
3.2.	4.2
3.3.	4.8
3.4.	4.8
4. Infrastructure and Facilities	
4.1.	4.6
4.2.	4.6
4.3.	4.4
4.4.	4.6
5. Power Usage Effectiveness (PUE)	

5.1.	4.6
5.2.	4.4
5.3.	4.6
5.4.	4
6. Operational Efficiency	
6.1.	4.2
6.2.	4.2
6.3.	4.4
6.4.	4.6
7. Scalability and Flexibility	
7.1.	4.2
7.2.	4.4
7.3.	3.8
7.4.	4
8. Customer Service and Support	
8.1.	4.6
8.2.	4.8
8.3.	4.4
8.4.	5
9. Environmental Impact and Sustainability	
9.1.	4.8
9.2.	4.8
9.3.	4.8

9.4.	4.8
10. AI Workload Optimization	
10.1.	4.2
10.2.	4.4
10.3.	3.8
10.4.	4
10.5.	4.8

- **Assessing Overall Quality**

To assess the overall quality of the data center for different workload scenarios, experts were asked to evaluate each quality factor for the following three options:

Option 1: No AI Workload

Option 2: 20-30% AI Workload

Option 3: 50% AI Workload

Each option has been assessed separately, and the collected responses are recorded below. (Scale: 1 = Poor, 5 = Excellent)

Survey Results: Data Center Quality Assessment in table 5.4

Table 5.4: Survey results: data center quality assessment

Factor	Option 1 (No AI Workload)	Option 2 (20-30% AI Workload)	Option 3 (50% AI Workload)
1. Tier Certifications			
1.1.	4.8	4.2	4.2
1.2.	4.8	5	5
1.3.	4.4	4	4
1.4.	4.2	4.8	4.8
2. Reliability and Uptime			
2.1.	5	4.2	4.2
2.2.	4.8	4.8	4.8
2.3.	4.4	4.8	4.8
2.4.	4.6	4.8	4.8
3. Security and Compliance			
3.1.	4.8	4.8	4.8
3.2.	4.4	4.6	4.6
3.3.	4.4	4.8	4.8
3.4.	4.6	4.8	4.8
4. Infrastructure and Facilities			
4.1.	4.8	4.4	4.4
4.2.	4.8	4.6	4.6
4.3.	4.6	4.4	4.4
4.4.	4.4	4.4	4.4

5. Power Usage Effectiveness (PUE)			
5.1.	4.2	4.2	4.2
5.2.	4.4	3.8	3.8
5.3.	3.8	4.4	4.4
5.4.	4.4	3.8	3.8
6. Operational Efficiency			
6.1.	4.6	4.2	4.2
6.2.	4.6	4.4	4.4
6.3.	4.8	4.8	4.8
6.4.	4.4	4.8	4.8
7. Scalability and Flexibility			
7.1.	5	4.6	4.6
7.2.	4.2	4.4	4.4
7.3.	4	4	4
7.4.	4.6	4.4	4.4
8. Customer Service and Support			
8.1.	4	4.6	4.6
8.2.	4.4	4.6	4.6
8.3.	4	4.2	4.2
8.4.	4.6	5	5
9. Environmental Impact and Sustainability			
9.1.	4.4	4.4	4.4
9.2.	4.2	4.4	4.4

9.3.	4	4	4
9.4.	4	4.6	4.6
10. AI Workload Optimization			
10.1.	0	4.4	4.4
10.2.	0	4.4	4.4
10.3.	0	4.4	4.4
10.4.	0	4.6	4.6
10.5.	0	4.2	4.2

Overall, the total quality assessment offers a comprehensive evaluation of each option, reflecting the effectiveness of the different configurations. This assessment considers the weighted importance of critical quality factors, ensuring an objective comparison. Table 5.5 below presents a summary of the overall quality levels for the three options, providing a basis for further analysis and decision-making.

Table 5.5: Total project quality estimates

Option	Total Score out of 5	Total Score out of 100
Option 1: No AI Workload	3.95	78.93
Option 2: 20-30% AI Workload	4.47	89.45
Option 3: 50% AI Workload	4.65	93.03

5.2.Efficiency Analysis Using Data Envelopment Analysis (DEA)

In this section, the efficiency of each data center configuration is evaluated using Data Envelopment Analysis (DEA). The analysis considers two inputs (Cost and Time) and one output (Quality) to determine the most efficient option.

5.2.1. Normalization

Before applying the DEA model, the input and output values are normalized to ensure fair comparison across different scales. The normalized values for **Cost**, **Time**, and **Quality** are presented in table 5.6 below:

Table 5.6: The normalized values for cost, time, and quality

Option	Normalized Cost	Normalized Time	Normalized Quality
Option 1: No AI Workload	0.313	0.453	0.522
Option 2: 20-30% AI Workload	0.554	0.631	0.591
Option 3: 50% AI Workload	0.771	0.631	0.615

5.2.2. DEA Efficiency Scores

Using the normalized values, the DEA model evaluates each option based on their efficiency in converting inputs (**Cost and Time**) into the desired output (**Quality**). The efficiency score is calculated for each option using the DEA model, with the most efficient option receiving a score of 1 (100%) and other options being ranked relative to it. In figure 5.7 below its presenting the results came out of the DEA model solved by the excel solver.

0. Reset

1. Data

2. Solution

3. Visualization

4. Solver

Info

F9

Figure 5.7: DEA excel solver results

The efficiency results are summarized in table 5.7 below:

Table 5.7: DEA efficiency scores

Option	DEA Efficiency Score	Ranking
Option 1: No AI Workload	100.00%	1
Option 2: 20-30% AI Workload	81.28%	3
Option 3: 50% AI Workload	84.58%	2

Based on the DEA results, **Option 1: No AI Workload** is the **most efficient data center configuration**, achieving the highest efficiency score compared to the other alternatives. This option balances cost, time, and quality, making it the preferred solution for deployment. The efficiency scores for each option are as follows: Option 1: 100%, Option 2: 81.28%, and Option 3: 84.58%. While Option 1 ranks the highest, Options 2 and 3 still demonstrate relatively high efficiency scores, indicating their potential viability depending on specific strategic priorities. When considering quality as the only output factor, Option 1 is still the most efficient because the difference in quality scores between AI and non-AI options is small. The slight quality improvement in AI-integrated options does not justify the higher costs and longer time requirements. The next section explores alternative scenarios to see how different weighting strategies and additional factors may affect efficiency evaluation.

5.3.Scenario Analysis

In the case of exploring different scenarios, the efficiency evaluation may change based on various factors. This section examines two scenarios that could influence the results.

5.3.1. Scenario 1: Cost Adjusted Over Time

Contrary to expectations of broad cost reductions through technological maturity, current trends and market analyses suggest that AI-related infrastructure costs are likely to increase over the next decade. This rise is driven by surging demand for high-performance GPUs, energy-intensive AI training workloads, global supply chain

constraints, and inflationary pressures on specialized components such as accelerators and cooling systems. However, the increase is not uniform across all infrastructure categories—costs for standard servers and networking equipment are expected to decline modestly due to continued commoditization and manufacturing scale. In this scenario, the DEA model is used to assess how the net effect of rising AI-specific costs and declining baseline hardware costs influences the relative efficiency of AI-integrated data center designs when cost is treated as a primary input.

1. Cost after 5 years

In the medium term, AI-related capital and operational expenditures are assumed to **increase by approximately 10–20%**, driven by escalating demand, constrained supply of advanced chips, and elevated energy consumption costs. This rise places additional financial pressure on data center designs incorporating AI, potentially lowering their DEA efficiency scores if output performance remains constant. While these cost increases are primarily associated with AI-specific infrastructures such as GPUs, accelerators, and advanced cooling systems, **the cost of standard servers and networking equipment is projected to decline modestly due to market maturity and large-scale production efficiencies**. As a result, the net cost varies depending on workload composition and infrastructure balance.

Key factors contributing to this cost increase may include:

- Price inflation in specialized GPUs (e.g., H100, B200)
- Higher cooling and power provisioning demands
- Increased scarcity of AI-optimized infrastructure components

In the figures 5.8 and 5.9 below, it explains the Adjustment in the total cost after 5 years by updating the cost of the materials for options 2 and 3.

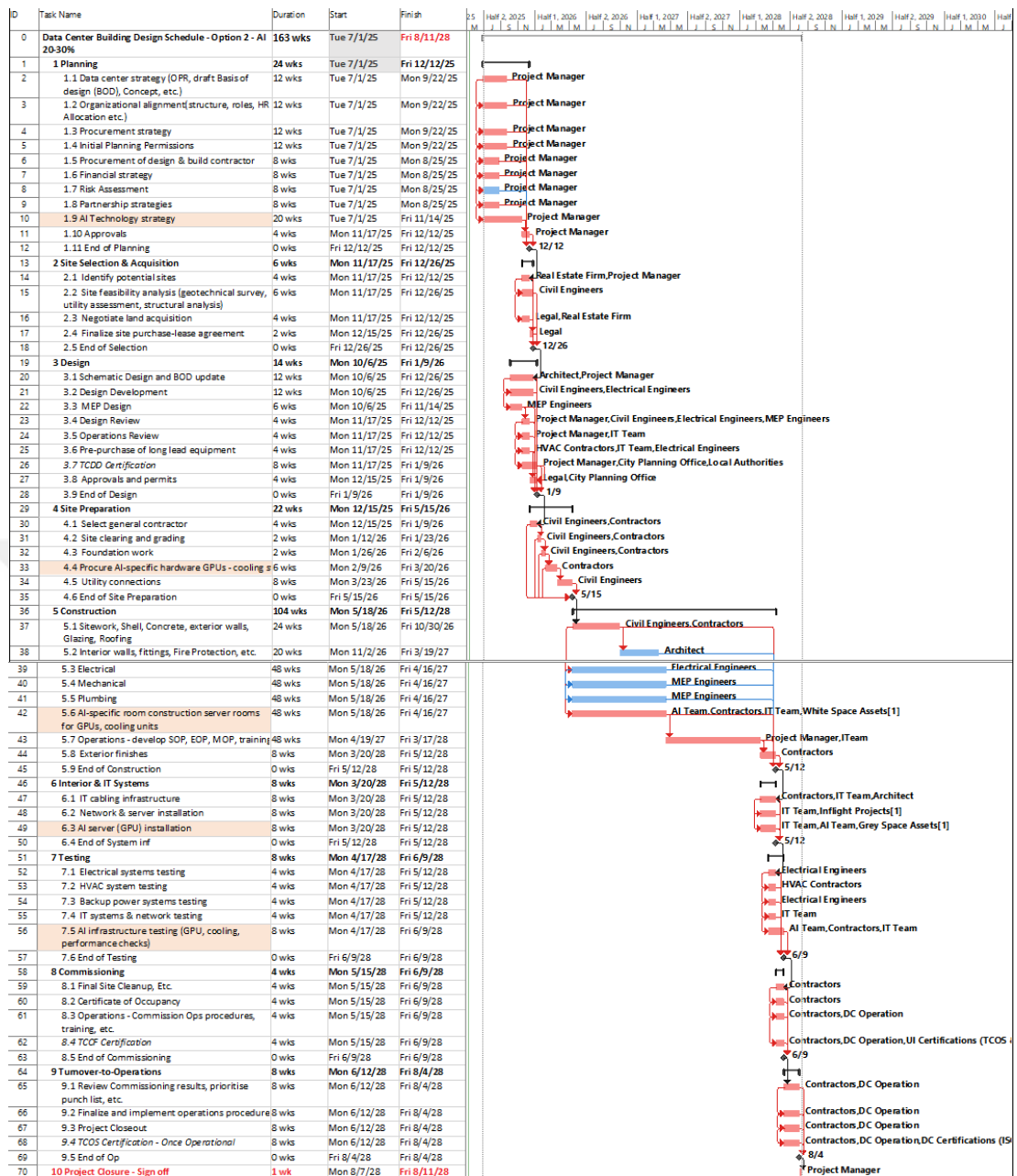


Figure 5.8: Scenario analysis – adjusted over time – after 5 years updated MS project schedule for option 2 – AI 20-30%

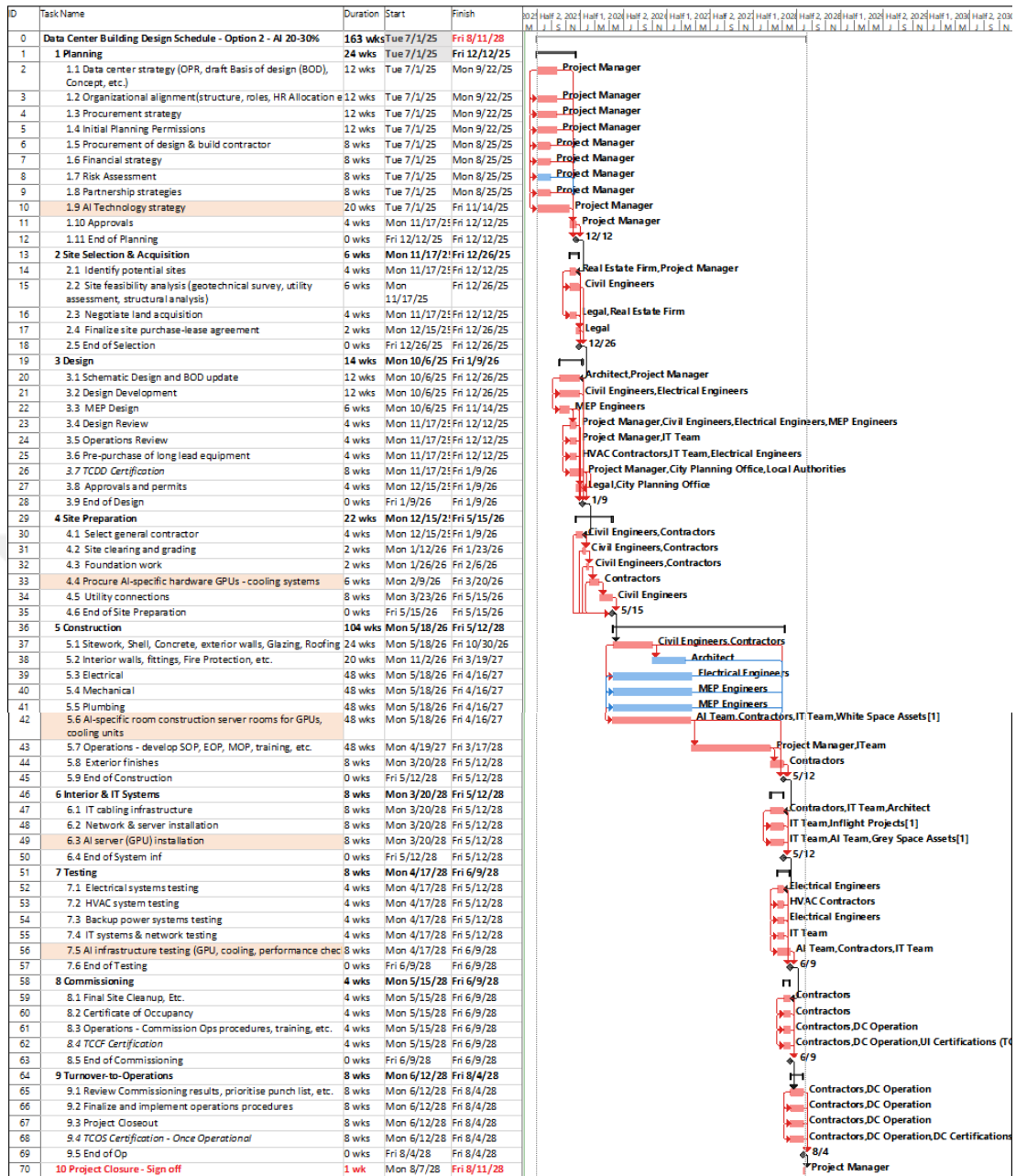


Figure 5.9: Scenario analysis – adjusted over time – after 5 years updated MS project schedule for option 3 – AI 50%

The table 5.8 below presents the updated DEA input values based on adjusted cost figures for this period:

Table 5.8. After 5 years adjusted costs

Option	Current Cost (\$)	Adjusted Cost (\$)
Option 1: No AI Workload	\$13,107,700	\$13,107,700 (No Change)
Option 2: 20-30% AI Workload	\$23,109,199	\$26,016,078
Option 3: 50% AI Workload	\$32,705,995	\$36,975,988

With the reduced cost assumption, the efficiency scores are updated in figure 5.10 and table 5.9:

DMU name	Efficiency Score	Efficiency Reference Set
DMU 1	100.00%	
DMU 2	81.23%	DMU 1
DMU 3	84.50%	DMU 1

Primal variables	Input parameter 1	Input parameter 2	Output parameter 1	BCC variable
DMU 1	0.0000	220.9480	191.4800	0.0000
DMU 2	0.0000	158.5946	137.4427	0.0000
DMU 3	0.0000	158.5946	137.4427	0.0000

Dual variables	DMU 1	DMU 2	DMU 3
lambda	1.0000	1.1316	1.1772
theta	0.0000	0.0000	0.0000
Dual objective	100.0000	81.2285	84.4995

Figure 5.10: After 5 dea excel solver results

Table 5.9: After 5 updated efficiency scores

Option	Adjusted Cost	Time (Input)	Quality (Output)	Efficiency Score
Option 1	\$13,107,700	117 Weeks	3.95	100.00%
Option 2	\$26,016,078	163 Weeks	4.47	81.23%
Option 3	\$36,975,988	163 Weeks	4.65	84.50%

2. Cost after 10 years

Over a longer 10-year horizon, the scenario assumes a **total cost increase of 35–50%** compared to current baseline levels. This project reflects sustained AI workload expansion, intensifying hardware requirements, and global competition for advanced manufacturing capacity. In the DEA context, such rising costs—if not offset by proportional gains in performance or ROI—may significantly diminish the relative efficiency of AI-heavy options. **While the costs associated with AI-specific infrastructure are expected to rise sharply, the price of standard servers and network equipment is anticipated to decline modestly, driven by technological maturity and supply chain stabilization.** This partial offset may slightly mitigate the overall cost burden in mixed infrastructure environments.

Additional long-term considerations:

- Continued rise in power usage effectiveness (PUE) due to dense AI racks
- Greater investment required for infrastructure redundancy and sustainability compliance
- Strategic risk of over-reliance on costly proprietary hardware solutions

In the figures 5.11 and 5.12 below, it explains the Adjustment in the total cost after 10 years by updating the cost of the materials for options 2 and 3.

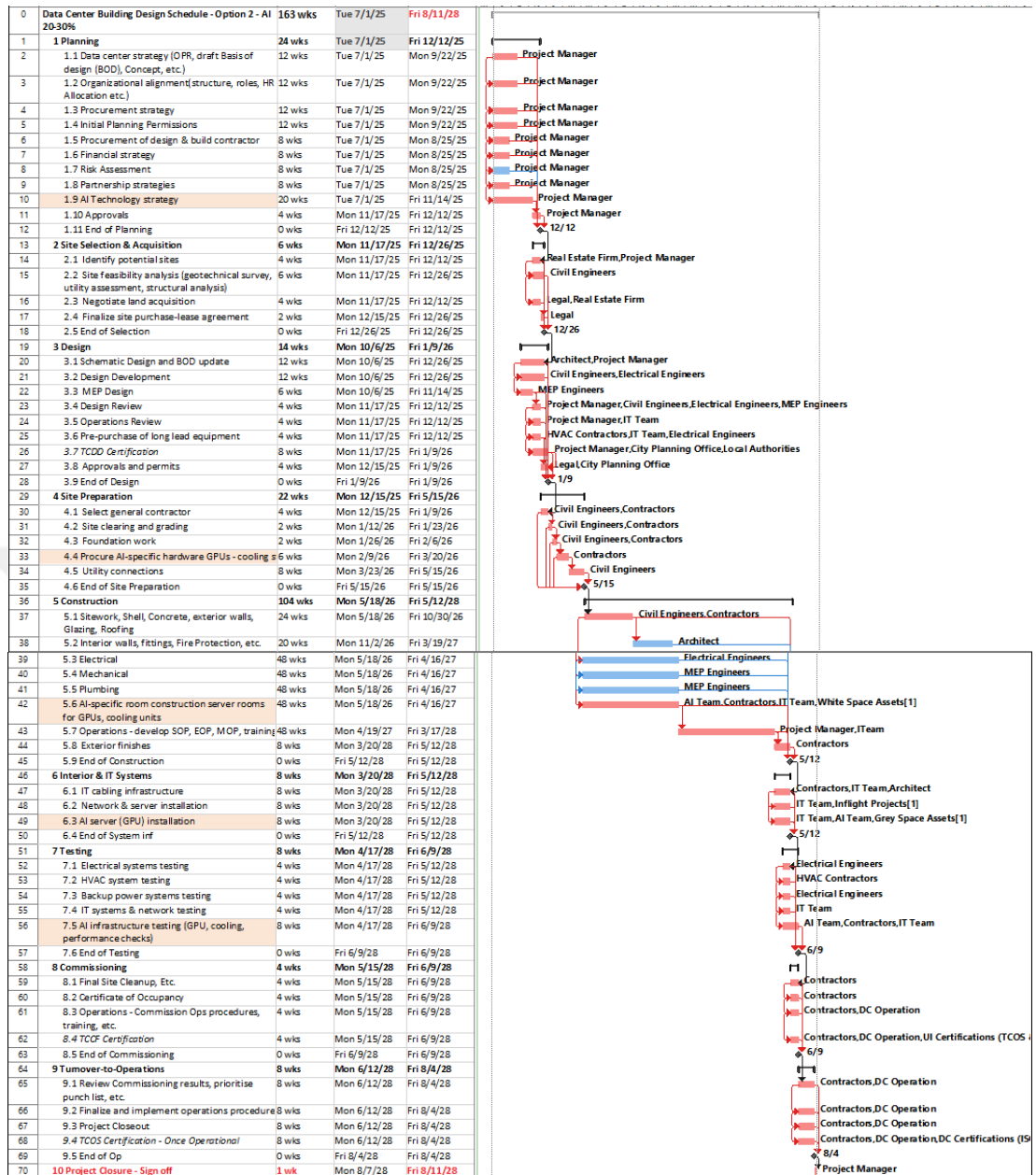


Figure 5.11: Scenario analysis – adjusted over time – after 10 years updated MS project schedule for option 2 – AI 20-30%



Figure 5.12: Scenario analysis – adjusted over time – after 10 years updated MS project schedule for option 3 – AI 50%

The table 5.10 below presents the updated DEA input values based on adjusted cost figures for this period:

Table 5.10: After 10 years adjusted costs

Option	Current Cost (\$)	Adjusted Cost (\$)
Option 1: No AI Workload	\$13,107,700	\$13,107,700 (No Change)
Option 2: 20-30% AI Workload	\$23,109,199	\$31,829,838
Option 3: 50% AI Workload	\$32,705,995	\$45,515,974

With the reduced cost assumption, the efficiency scores are updated in figure 5.13 and table 5.11:

DMU name	Efficiency Score	Efficiency Reference Set
DMU 1	100.00%	
DMU 2	81.23%	DMU 1
DMU 3	84.50%	DMU 1

Primal variables	Input parameter 1	Input parameter 2	Output parameter 1	BCC variable	Primal objective	Normalisation constraints	DMU 1	DMU 2	DMU 3
DMU 1	0.0000	220.9980	191.4800	0.0000	100.0000	100.0000	0.0000	26.1517	21.5947
DMU 2	0.0000	158.5946	137.4427	0.0000	81.2285	100.0000	0.0000	18.7715	15.5005
DMU 3	0.0000	158.5946	137.4427	0.0000	84.4995	100.0000	0.0000	18.7715	15.5005

Dual variables	DMU 1	DMU 2	DMU 3	Input parameter 1	Input parameter 2	Output parameter 1	Lambda normalisation
lambda	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
theta	1.0000	0.8123	0.8450	0.2054	0.0000	0.0000	1.1316
Dual objective	100.0000	81.2285	84.4995	0.4146	0.0000	0.0000	1.1772

Figure 5.13: After 10 DEA excel solver results

Table 5.11: After 10 updated efficiency scores

Option	Adjusted Cost	Time (Input)	Quality (Output)	Efficiency Score
Option 1	\$13,107,700	117 Weeks	3.9 5	100.00%
Option 2	\$31,829,838	163 Weeks	4.47	81.23%
Option 3	\$45,515,974	163 Weeks	4.65	84.50%

The updated DEA results under the cost increase scenario reveal a noticeable decline in the efficiency scores of AI-integrated data center options compared to the baseline. As projected costs rise in both the 5-year and 10-year horizons—particularly for AI-specific components, the relative efficiency of these configurations diminishes when outputs such as quality and time remain constant. In contrast, data center designs with minimal or **no AI workload maintain higher efficiency scores due to their lower cost burden**. This scenario highlights the sensitivity of DEA outcomes to cost fluctuations and underscores the financial risks associated with large-scale AI integration in data centers. AI-heavy infrastructure may become less efficient from a resource utilization perspective. Therefore, decision-makers should carefully assess long-term cost trajectories and consider hybrid workload **strategies or delayed AI adoption to preserve efficiency and manage risk**.

5.3.2. Scenario 2: Assessing Efficiency with ROI as an Output

In scenario 2 assuming if **Return on Investment (ROI)** is included as an additional output alongside quality, the efficiency evaluation considers both operational performance and financial returns. AI-integrated options may appear more efficient if their higher initial costs lead to greater long-term financial benefits. This scenario provides a broader assessment by incorporating financial sustainability into the efficiency analysis. Using the new efficiency model incorporating **ROI** as output, the efficiency scores are recalculated after 10 years of investment presented in figure 5.14 and table 5.12:

DMU name	Efficiency Score	Efficiency Reference Set
DMU 1	100.0000	
DMU 2	75.225% DMU 1	
DMU 3	79.385% DMU 1	

Primal variables	Input parameter 1	Input parameter 2	Output parameter 1	Output parameter 2	BCC variable
DMU 1	100.0000	220.9846	178.4017	0.0000	0.0000
DMU 2	766.0173	0.0000	0.0000	131.3506	0.0000
DMU 3	0.0000	158.5946	0.0000	130.5448	0.0000

Primal objective	Normalisation constraints	DMU 1	DMU 2	DMU 3
100.0000	100.0000	0.0000	37.0940	32.6496
75.2169	100.0000	0.0000	24.7831	31.2404
79.3808	100.0000	0.0000	25.2445	20.6192

Dual variables	DMU 1	DMU 2	DMU 3
lambda	1.0000	1.0415	1.1059
theta	0.0000	0.0000	0.0000
Dual objective	100.0000	75.2169	79.3808

Dual constraints	Input parameter 1	Input parameter 2	Output parameter 1	Output parameter 2	Lambda normalisation
0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
0.0000	0.0029	0.0108	0.0000	0.0000	1.0415
0.0502	0.0000	0.0220	0.0000	0.0000	1.1059

Figure 5.14: DEA excel solver results (including ROI as output)

Table 5.12: Updated efficiency scores (including ROI as output)

Option	Cost	Time	Quality	ROI	DEA Results
Option 1: No AI Workload	\$13,107,700	117 Weeks	3.95	20.6%	100.00%
Option 2: 20-30% AI Workload	\$23,109,199.00	163 Weeks	4.47	21.5%	75.22%
Option 3: 50% AI Workload	\$32,705,995.00	163 Weeks	4.65	22.5%	79.38%

These results indicate that while AI-integrated data center options can offer higher revenue potential, their efficiency is significantly influenced by the return on investment. To justify the increased capital and operational expenditures associated with AI workloads, the ROI must be substantial, with a break-even point ideally achieved within a year. This urgency is underscored by the rapid evolution of AI technologies, which can render existing models obsolete quickly.

6. CONCLUSION

This thesis examines the efficiency of AI workload integration within data centers by applying a project management approach and employing Data Envelopment Analysis (DEA) to assess cost, time, and quality. The study aims to determine whether hosting AI workloads in data centers enhances operational efficiency and project management effectiveness. By analyzing multiple workload scenarios, the research identifies key factors affecting efficiency, including cost minimization, time optimization, and quality maximization. The research problem addresses whether AI workload integration improves project efficiency in data centers and how project management methodologies, such as Waterfall, can support their design. The findings confirm that AI-enhanced workloads lead to improved quality performance; however, the differences in quality among the options remain relatively small. At the same time, AI workloads introduce significantly higher costs and extended timelines, which require careful strategic planning. The DEA results indicate that **Option 1 (No AI workload)** is the most efficient due to its optimal balance of cost, time, and quality. While **Options 2 and 3 (with 20–30% and 50% AI workloads, respectively)** achieve marginally higher quality, their increased operational and capital costs lower their overall efficiency scores. Nonetheless, these AI-integrated options still demonstrate viable efficiency under specific conditions. To further investigate these conditions, two additional scenarios were developed: **Scenario 1 (Cost Increase Over Time):** Rising AI infrastructure costs over 5- and 10-year horizons showed a further decline in the efficiency of AI-based options, reinforcing the importance of cost sensitivity in long-term planning. Although standard server and network equipment costs are expected to decrease, this reduction does not fully offset the growing burden of AI-related expenses. **Scenario 2 (Integrating ROI into DEA):** Incorporating ROI as an output factor significantly altered the efficiency landscape. While Option 1 retained full efficiency (100%), Options 2 and 3 dropped to 75.22% and 79.38%, respectively. These results underscore that for AI-integrated data centers to be viable, the return on investment must be high, and the financial breakeven should ideally occur within a year. This urgency is driven by rapid AI hardware evolution, which can render systems obsolete before recovering costs. **Based on these findings**, the study recommends a balanced deployment strategy: develop **traditional (non-AI) data center capacity for**

80–90% of total design, while reserving **10–20% for AI workloads**, allowing room for future adaptation as technologies mature and economic conditions become more favorable. Future research could explore additional efficiency metrics, such as environmental sustainability, long-term operational costs, and AI workload-specific performance measures. Incorporating real-world deployment data and simulating alternative project management approaches could also help validate and expand on the findings presented in this study.



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APPENDIX A_ FIRST SURVEY: WEIGHT DATA CENTER QUALITY EVALUATION SURVEY

Questions Responses Settings

Section 1 of 11

First Survey: Weight Data Center Quality Evaluation Survey

Purpose:
This survey aims to evaluate the quality of data centers across multiple dimensions. Your expert insights will help assess the strengths and areas for improvement in data center operations, infrastructure, and security.

Instructions:
Please rate the importunacy of each statement from 1 to 5, where:

- 1 = Strongly Important
- 2 = Important
- 3 = Neutral Important
- 4 = Not Important
- 5 = Strongly Not Important

Name

Short-answer text

Email

Short-answer text

After section 1 Continue to next section

Section 2 of 11

Tier Certifications

Description (optional)

1

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4

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DC must meet or exceed the Tier Certifications requirements. (e.g., Tier I-IV).

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The data center must have the level of redundancy and fault-tolerance align with its Tier Certification.

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The facility must demonstrate compliance with Uptime Institute standards for its Tier level.

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There are must clear plans and processes in place to maintain or upgrade Tier Certification as needed.

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After section 2 Continue to next section

Reliability and Uptime

Description (optional)

The data center must meet industry standards for up-time (e.g., 99.99% or higher).

1	2	3	4	5
☐	☐	☐	☐	☐

There must be efficient generators in place for backup power and cooling systems.

1	2	3	4	5
☐	☐	☐	☐	☐

The data center must provide a high level of redundancy to minimize service interruptions.

1	2	3	4	5
☐	☐	☐	☐	☐

The downtime must incidents minimal and handled efficiently.

1	2	3	4	5
☐	☐	☐	☐	☐



Section 4 of 11

Security and Compliance

Description (optional)

The data center must have robust physical security measures (e.g., surveillance, access control).

- | | | | | |
|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

The data center must adhere to industry standards and compliance frameworks (e.g., ISO 27001, PCI DSS).

- | | | | | |
|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

The cybersecurity protocol must frequently be updated and tested.

- | | | | | |
|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

The Staff must receive regular training in data security policies.

- | | | | | |
|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

After section 4 Continue to next section



Section 5 of 11

Infrastructure and Facilities

Description (optional)

The data center must be well-maintained, with modern, reliable infrastructure.

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Cooling systems must have energy-efficient and provide sufficient environmental control.

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Cabling and rack organization must be optimized for accessibility and scalability.

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The data center layout must be supporting the efficient power distribution and load management

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After section 5 Continue to next section

Section 6 of 11

Power Usage Effectiveness (PUE)



Description (optional)

The data center regularly must track and report its PUE to evaluate energy efficiency.

1	2	3	4	5
☐	☐	☐	☐	☐

The facility's PUE score must meet or exceed industry standards for data centers of similar size and capacity.

1	2	3	4	5
☐	☐	☐	☐	☐

The efforts must be in place to improve PUE over time through enhanced cooling and power management.

1	2	3	4	5
☐	☐	☐	☐	☐

The data center's must be design incorporates best practices to maintain a low PUE, indicating strong energy efficiency.

1	2	3	4	5
☐	☐	☐	☐	☐

Section 7 of 11

Operational Efficiency

Description (optional)

The data center must use automation and monitoring tools effectively to optimize performance.

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Energy efficiency must be a priority, with regular assessments to reduce power usage.

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Capacity planning must be managed proactively to meet future demand.

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The data center staff must demonstrate high levels of expertise and efficiency

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After section 7

Continue to next section

Section 8 of 11

Scalability and Flexibility

Description (optional)

The data center must accommodate growth without major disruptions.

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There must be a scalable infrastructure solution to support evolving technological needs.

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The data center must allow for flexible customer solutions (e.g., hybrid cloud, colocation).

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The data center's design must support rapid deployment of new services

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After section 8 Continue to next section

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The data center must offer reliable, accessible, and timely customer support.

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1 2 3 4 5

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1 2 3 4 5

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1 2 3 4 5

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Environmental Impact and Sustainability

Description (optional)



The data center actively must work to reduce its carbon footprint.

- | | | | | |
|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

Renewable energy sources must be used whenever possible.

- | | | | | |
|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

Waste management practices must align with industry sustainability standards.

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|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

The data center must commit to sustainable growth and resource efficiency.

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|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
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Section 11 of 11

AI Workload Optimization



Description (optional)

The data center must support GPU-based infrastructure and AI-specific hardware effectively.

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|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

Cooling systems must be optimized for the higher thermal demands of AI workloads.

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|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

Network infrastructure must ensure low latency and high bandwidth for AI processing.

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|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1 | 2 | 3 | 4 | 5 |
| ☐ | ☐ | ☐ | ☐ | ☐ |

Scalable solutions must be available to meet varying AI computational demands.

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| 1 | 2 | 3 | 4 | 5 |
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Energy efficiency must be maintained despite AI's intensive power requirements.

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| 1 | 2 | 3 | 4 | 5 |
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APPENDIX B_SECOND SURVEY: DATA CENTER QUALITY EVALUATION SURVEY

Questions

Responses 9

Settings

Section 1 of 11

Second Survey: Data Center Quality Evaluation Survey

B I U ↺ ↻

Purpose:
This survey aims to evaluate the quality of data centers across multiple dimensions. Your expert insights will help assess the strengths and areas for improvement in data center operations, infrastructure, and security.

Instructions:
Please rate the tare of each statement from 1 to 5, based on each project, where:

- 1 = Strongly High
- 2 = High
- 3 = Neutral
- 4 = Low
- 5 = Strongly Low

Name

Short-answer text

Project Name

☐ Standard Workload Capacity (No AI Workload)

☐ Hybrid Workload (20-30% AI Focus)

☐ High AI Workload (50% AI Focus)

After section 1 Continue to next section

Section 2 of 11

Tier Certifications

Description (optional)

DC must meet or exceed the Tier Certifications requirements. (e.g., Tier I-IV).

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The data center must have the level of redundancy and fault-tolerance align with its Tier Certification.

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The facility must demonstrate compliance with Uptime Institute standards for its Tier level.

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There are must clear plans and processes in place to maintain or upgrade Tier Certification as needed.

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After section 2

Continue to next section

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**Reliability and Uptime**

Description (optional)

The data center must meet industry standards for up-time (e.g., 99.99% or higher).

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There must be efficient generators in place for backup power and cooling systems.

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The data center must provide a high level of redundancy to minimize service interruptions.

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The downtime must incidents minimal and handled efficiently.

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Section 4 of 11

Security and Compliance



Description (optional)



The data center must have robust physical security measures (e.g., surveillance, access control).

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The data center must adhere to industry standards and compliance frameworks (e.g., ISO 27001, PCI DSS).

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The cybersecurity protocol must frequently be updated and tested.

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The Staff must receive regular training in data security policies.

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After section 4 Continue to next section



Section 5 of 11

Infrastructure and Facilities

Description (optional)

The data center must be well-maintained, with modern, reliable infrastructure.

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Cooling systems must have energy-efficient and provide sufficient environmental control.

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Cabling and rack organization must be optimized for accessibility and scalability.

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The data center layout must be supporting the efficient power distribution and load management

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After section 5

Continue to next section

Section 6 of 11

Power Usage Effectiveness (PUE)

Description (optional)

The data center regularly must track and report its PUE to evaluate energy efficiency.

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The facility's PUE score must meet or exceed industry standards for data centers of similar size and capacity.

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The efforts must be in place to improve PUE over time through enhanced cooling and power management.

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The data center's must be design incorporates best practices to maintain a low PUE, indicating strong energy efficiency.

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After section 6 Continue to next section

Section 7 of 11

Operational Efficiency

Description (optional)

The data center must use automation and monitoring tools effectively to optimize performance.

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Energy efficiency must be a priority, with regular assessments to reduce power usage.

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Capacity planning must be managed proactively to meet future demand.

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The data center staff must demonstrate high levels of expertise and efficiency

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After section 7

Continue to next section

Section 8 of 11

Scalability and Flexibility

Description (optional)

The data center must accommodate growth without major disruptions.

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There must be a scalable infrastructure solution to support evolving technological needs.

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The data center must allow for flexible customer solutions (e.g., hybrid cloud, colocation).

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The data center's design must support rapid deployment of new services

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After section 8

Continue to next section

Section 9 of 11

Customer Service and Support

Description (optional)

The data center must offer reliable, accessible, and timely customer support.

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Communication with clients must be clear, transparent, and proactive.

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The data center regularly must seek feedback from clients to improve services.

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SLAs (Service Level Agreements) must be clear and consistently met.

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After section 9 Continue to next section

Section 10 of 11

Environmental Impact and Sustainability

Description (optional)

The data center actively must work to reduce its carbon footprint.

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Renewable energy sources must be used whenever possible.

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Waste management practices must align with industry sustainability standards.

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The data center must commit to sustainable growth and resource efficiency.

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After section 10 Go to section 11 (AI Workload Optimization)

AI Workload Optimization



Description (optional)



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The data center must support GPU-based infrastructure and AI-specific hardware effectively.

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Cooling systems must be optimized for the higher thermal demands of AI workloads.

1	2	3	4	5
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Network infrastructure must ensure low latency and high bandwidth for AI processing.

1	2	3	4	5
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Scalable solutions must be available to meet varying AI computational demands.

1	2	3	4	5
☐	☐	☐	☐	☐

Energy efficiency must be maintained despite AI's intensive power requirements.

1	2	3	4	5
☐	☐	☐	☐	☐