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(REVIEW ARTICLE)

AI-GUIDED ORCHESTRATION FOR SECURE AND COST-OPTIMIZED MULTI-CLOUD MIGRATIONS

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ABSTRACT

Artificial intelligence has become an increasingly important enabler of enterprise cloud modernization because migration decisions involve simultaneous trade-offs among security posture, service continuity, vendor concentration, workload placement, and lifecycle cost. In single-provider contexts, migration planning may be based on comparatively limited assumptions in terms of interface, pricing and governance models. This is not the case in multi-cloud environments, where orchestration becomes a continuous optimization problem rather than a one-time relocation exercise. This review examines AI-guided orchestration for secure and cost-efficient workload migration across multiple clouds, drawing on literature on cloud-migration decision support, multi-cloud brokerage, workload placement, risk analysis, predictive provisioning, and learning-based scheduling. Some of the key themes are migration evaluation, provider selection, workload characterization, security-aware placement, reinforcement-learning-based resource management, and heterogeneous-pricing and policy-constrained cost modelling. The reviewed studies suggest that orchestration quality depends not only on optimization algorithms, but also on migration-stage visibility, metadata quality, portability constraints, and governance integration. Important unresolved gaps include incomplete integration of compliance logic into orchestration engines, inadequate handling of post-migration drift, limited explainability of AI-generated decisions, and weak empirical validation across heterogeneous provider combinations. This area is strategically important because large-scale cloud modernization increasingly depends on coordinated, adaptive, and policy-conscious automation capable of sustaining resilience while reducing economic inefficiency and migration risk.

Keywords*:* Artificial Intelligence; Cloud Migration; Cost Optimization; Multi-Cloud; Orchestration; Security

1 INTRODUCTION

Cloud migration has increasingly become a process of architectural transformation rather than simple infrastructure replacement, involving application decomposition, data movement, service-brokerage decisions, governance redesign, and operating-model change. The initial analysis of migration concluded that it takes much more than technical replication of current workloads on remote services to transfer legacy systems into the cloud environment. Migration affects software architecture, operational dependencies, quality attributes, and long-term maintainability, especially when business-critical applications remain tightly coupled to on-premises assumptions [1]. Subsequent decision-oriented studies extended this argument by showing that migration decisions depend on technological, organizational, and environmental factors rather than on cost expectations alone, thereby framing cloud adoption as a strategic, technical, and risk-laden undertaking [2]. As cloud ecosystems have matured, the problem space has expanded through

the emergence of multi-cloud-native application models, cross-provider composition, portability requirements, and orchestration complexity across heterogeneous control planes [3]. The existing body of knowledge especially regards migration as a less stable destination choice and more of an adaptive systems-engineering problem.

The importance of the topic has been accelerated by the fact that numerous businesses are no longer migrating to a single cloud, but to mixed environments of hyperscale public clouds, specialized data services, regional providers, sovereign cloud zones, and existing private infrastructure. Multi-cloud adoption is often motivated by resilience, jurisdictional flexibility, bargaining leverage, latency control, and the desire to avoid lock-in. However, these advantages result in a similar orchestration load. Providers differ significantly in resource abstractions, billing models, trust assumptions, network topology, identity layers, and regulatory controls. A migration plan that disregards such differences runs the risk of replacing one form of rigidity with another. Reviews of cloud-resource orchestration indicate that multi-cloud environments require frameworks capable of discovering, selecting, allocating, and managing heterogeneous resources across providers while preserving application requirements and operational intent [4]. Simultaneously, cloud migration risk studies have noted that information security risk, data-access risk, virtual-machine-related risk, compliance risk, financial risk, and managerial failure are the key points of migration frailty [5]. Those findings indicate that orchestration quality becomes an important determinant of migration success.

Artificial intelligence has come into this field due to the fact that manual orchestration is not sufficient where migration portfolios contain variable workloads, uncertain demand, differentiated service-level goals and security regulations as well as dynamic cloud-pricing. Small-scale provider selection can be supported by conventional heuristics and fixed sets of rules, but larger scale migrations are causing an increasing demand on predictive and adaptive decision support. Database-centred approaches can estimate migration duration and future running cost from workload models. During early adoption planning, knowledge-based migration support can organize the goal-obstacle analysis [8]. Reviews of machine-learning-based resource management show that cloud control increasingly involves workload estimation, task scheduling, provisioning, placement, and energy optimization, with learning-centric approaches becoming more prominent in dynamic environments [17]. The more recent reviews of deep reinforcement learning in cloud scheduling yield that learning-based orchestration is specifically appealing due to the large state spaces, turbulent environments, and conflicting goals of cost, latency, utilization, and service quality introduced by the cloud environment [19]. The discipline is hence shifted towards orchestration intelligence as opposed to mere migration automation.

Security is also an additional complication since migration routes tend to introduce short-lived windows of exposure as contrasted with consistent runtime risk. Identity federation, transfer channels, jurisdictional boundaries, trust boundaries, key management, logging consistency, and policy inheritance can differ across providers and across migration phases. Minimal studies have begun to address the optimization of secure multi-cloud allocation, and it has been demonstrated that orchestration logic cannot use security as a checklist that can be checked once the placement decisions have been made [20]. Meanwhile, architecture-oriented migration reviews note that quality concerns remain underdeveloped in many migration systems, particularly after migration is complete and cloud-native reconfiguration begins [6]. This circumscription is also consequential since secure migration is not only a transport problem but an ongoing governance and placement problem that commences with assessment up to post-migration operation.

A similar evolution can be observed in cost optimization. The initial study of multi-cloud brokerage focused on the placement of virtual machines optimally to suppliers with respect to performance and financial cost [11]. Later scheduling research has shown that the deployment of services on multiple clouds can be optimized when response to various constraints and strategies are at work [10]. More recent application-based optimization and multi-cloud brokering has pointed out that the control of costs will be much harder in hybrid and multi-cloud contexts since infrastructure costs, platform costs, and software costs will vary across architectural interrelation and among changing resource configurations [12]. Cost can no longer be reduced to simple instance-price comparison. It entails the overhead of migration, data transfer, redundancy planning, observability cost, scaling policy behavior, licensing, storage tiering and security related controls the financial impact of which may manifest post cutover. Cost-conscious orchestration in multi-cloud migration should make predictions on the structural impact and not just reduce deployment cost in the early stages.

This review examines the role of AI-assisted orchestration in enabling secure and cost-efficient multi-cloud migration, with particular attention to the interaction among migration assessment, brokerage, learning-based resource management, and policy-aware placement. The literature is first thematically reviewed, then an organization of the key conceptual and methodological approaches employed in this area is provided and then a discussion of reported findings, trade-offs, limitations, and gaps in research proceeds. The review concludes by suggesting future directions for moving beyond fragmented migration tooling toward more flexible, interpretable, and governable orchestration of heterogeneous cloud estates.

2 LITERATURE REVIEW

The literature on AI-informed orchestration for multi-cloud migration does not derive from a single tradition, but from several parallel streams. One of the streams deals with migration as such, the questions that are being discussed are why organizations migrate, how decision structures are organized, and what risks emerge at pre-migration, migration, and post-migration levels. Systematic migration studies show that legacy-to-cloud migration should be treated as architectural transformation with post-migration quality implications, rather than as simple workload transfer to hosted systems [1], [6]. The organizational decision studies added that the intent to migrate is determined by technological preparedness, the ability of the organization and the environmental strains [2]. The risk-oriented literature at the time categorized the threats of migration under security, data access, virtualization, provider selection, legal compliance, financial exposure and managerial failure of the migration as an essential part of migration planning [5]. This literature does not necessarily integrate AI methods per se, but they define the problem boundaries which would be later taken care of by orchestration models.

Another research stream concerns multi-cloud architecture and orchestration. Studies of multi-cloud-native applications have focused on portability logic, service decoupling, infrastructure abstraction, and orchestration patterns that allow applications to operate across non-homogeneous providers as part of architectural design [3]. Organized reviews of cloud resource coordination broadened regarding that point of view by defining the capabilities anticipated of multi-cloud coordination stages, such as finding, brokering, provisioning, interoperability managing, monitoring, and lifecycle supervision [4]. The significance of this literature is that the process of migrating into multi-cloud environments is hardly a one-cutover event. It is typically a gradual shift where workloads, data stores and control functions are gradually shifted or rearranged. Consequently, orchestration is required to be dynamically operated at the coexistence times, rollback window, and post-migration optimization. Multi-cloud orchestration studies have thus taken focus into securing the migration process even when the migration process is not the exclusive focus of study.

A third stream is concerned with the evaluation of workload and database migration. The work on database-centred research added the model-based methods of estimating the costs of migration, time, and subsequent operating cost given workload records and schema attributes, and thus, shifted the migration planning model to evidence-based decision support [7]. Similar research on knowledge-reuse suggested organized migration goal repositories, migration barriers, and mitigation strategies to enhance initial analysis [8]. This work is particularly relevant to AI-guided orchestration because learning-based systems require well-defined states and decision variables. In the absence of workload characterization, dependency knowledge and migration constraints, sophisticated orchestration degenerates to reactive placement created in a strategic context. The literature thus indicates that clever orchestration starts with the quality of representation: the more the quality with which migration state is approximated is high the more plausible the resultant optimization will be.

The fourth stream is the multi-cloud brokerage and service selection in awareness of the cost. Brokering research showed that optimized placement of virtual resources across multiple providers can improve both cost and performance relative to single-provider deployment [11]. Subsequent scheduling research formulated deployment plans of the best deployment of services on various clouds [10]. This was followed by application-based brokering where mixed-integer programming methods were formalized to add a service measuring attribute, law limitation, location criteria and cost reduction as part of optimization deployment planning [12]. Subsequent studies by brokerages optimized this line with hybrid service brokering, normalization of costs to performance and combined weighted approaches to the multi-provider selection of services [13-15]. The general conclusion made in these studies is that the optimization of costs of multi-cloud migration cannot be achieved without ranking of the services, filtering by the providers and placing them based on constraints. The brokerage heritage of the AI guided orchestration is even present when classical optimization procedures are discontinued or augmented with learning-based models.

A fifth stream looks into adaptive provisioning and AI resource management. Dynamic provisioning using Bayesian learning techniques demonstrated how cloud applications can use proactive resource estimation as compared to reactive scaling only [16]. Reviews of machine-learning-based resource management and machine-learning approaches in hybrid cloud paradigms were reported to record the growth of learning approaches in the domains of workload predictability, task scheduling, VM consolidation, placement, and energy management [17-18]. Broader reviews of deep reinforcement learning in the context of cloud scheduling contended that learning-based approaches are most appealing in dynamic cloud conditions where optimization targets are nonlinear and state space is large and operating conditions evolve sharply [19]. Even though significant parts of this literature are not migration-specific, its methodological impact is quite relevant: post-migration operations are more and more reliant on constant adjustment, and the success of migration is determined by whether orchestration can effectively deal with the destination milieu after cutover.

A sixth stream ensures security and adaptive allocation are more incorporated. The secure multi-cloud resource allocation research work has integrated authentication-conscious policies with optimization-oriented resource

scheduling, which means that orchestration may need to incorporate security controls rather than invoke them as independent post-hoc checks [20]. Multi-agent allocation models, based on reinforcement learning, have also handled the allocation decision in cloud architecture of changing demand, energy consumption, and resource release decision-making [21]. The specific models of resource-allocation-as-a-service of various cloud providers also demonstrate that SLA-driven allocation is possible as a multi-provider decision layer as opposed to being a local scheduling facility [22]. Combinations of the literature suggest that the use of AI as a guiding tool in the safe and cost-efficient relocation process ceases to be a hypothetical dream. The required components already exist in the research base but are still in bits that are scattered throughout the migration assessment, brokerage and cost modelling, resource management and secure allocation traditions.

Table 1: Summary of key findings

Ref	Focus	Key Findings
[6]	Legacy-to-cloud migration from an architectural perspective	Identified migration motivations, target cloud architecture patterns, and post-migration quality concerns, highlighting insufficient attention to quality assurance after transition.
[7]	Database migration evaluation using workload models	Proposed a two-stage workload and structure modelling approach that estimated migration duration, migration cost, and future running cost with reported relative error between 4% and 22% in real migrations.
[8]	Knowledge reuse for cloud migration adoption	Developed a goal-obstacle and countermeasure repository that structures early migration analysis and supports more systematic planning of cloud adoption pathways.
[9]	Cost optimization in dual cloud-based storage architecture	Formulated storage-placement decisions under dual-cloud conditions, showing that transfer and storage choices materially affect total expenditure over time.
[10]	Scheduling strategies across multiple clouds	Demonstrated that alternative scheduling strategies materially influence deployment quality under differing optimization criteria and user constraints.
[11]	Brokering for VM placement across multiple providers	Showed that optimized multi-provider placement can improve cost and performance relative to single-provider allocation.
[12]	Application-based brokering in heterogeneous clouds	Used mixed-integer programming and Bender's decomposition to generate cost-optimized deployment plans under service, jurisdictional, and logical constraints.
[13]	Hybrid service brokering for multi-cloud architectures	Reported improvements in response time, data-centre processing time, and monetary cost through normalized cost-performance-aware brokering.
[14]	Cloud service broker approaches and challenges	Classified broker models and identified persistent gaps in service comparison, interoperability, and decision support depth.
[15]	Integrated-weighting broker model in cloud environments	Presented a broker model for service selection under multiple criteria, strengthening decision support for heterogeneous cloud offerings.
[16]	Bayesian dynamic provisioning for service-based cloud applications	Combined autonomic computing with predictive learning to support proactive provisioning under variable workloads.
[20]	Secure multi-cloud allocation with adaptive authentication	Integrated authentication and allocation logic, reporting high efficiency and security outcomes while foregrounding security-aware placement.

Table 1 indicates that convergence and not replacement have been achieved in research development. Migration studies address adjacent components of the orchestration problem, brokerage models, learning-based schedulers and secure allocation systems. The table also shows another pattern of limitation many studies will optimize one layer well, which presumes that the other layers are held constant, although in reality the migration programs are being determined by interactions between all the layers.

3 METHODOLOGY

This review was conducted as a narrative synthesis of literature on AI-guided orchestration, cloud migration, multi-cloud brokerage, and learning-based resource management, covering publications from 2012 to 2024. Literature was identified through searches of IEEE Xplore, Scopus, ACM Digital Library, and Google Scholar using the following term combinations: “cloud migration orchestration”, “multi-cloud workload placement”, “AI cloud resource management”, “cloud migration risk”, “cloud service brokerage cost optimization”, “reinforcement learning cloud scheduling”, “secure multi-cloud allocation”, and “machine learning cloud provisioning”. Papers were included if they (a) addressed orchestration, placement, brokerage, provisioning, or migration decision-making in cloud or multi-cloud contexts, (b) reported empirical evaluation, simulation results, or systematic analysis, and (c) were published in peer-reviewed journals or conference proceedings. Papers were excluded if they addressed cloud topics without relevance to orchestration or migration logic, or if they were unavailable in full text. Foundational migration studies were included selectively to define the problem scope addressed by AI-guided approaches. The final corpus comprises 22 primary sources synthesized thematically across six streams: migration analysis, multi-cloud architecture and orchestration, workload and database evaluation, multi-cloud brokerage, adaptive provisioning and AI resource management, and security-integrated allocation. The review follows narrative synthesis conventions and does not employ formal meta-analytic aggregation, given the substantial heterogeneity in evaluation environments and optimization goals across the reviewed studies.

The methodological approaches in this area can be organized as a staged orchestration logic spanning pre-migration analysis, migration execution, and post-migration operation. Migration intelligence acquisition is the first stage and involves inventory extraction, identifying workload dependencies, policy discovery, and defining the target-state. The second phase is feasibility and risk analysis, in which the candidate providers, type of service, and architectural patterns are analyzed based on the cost, security, compliance and the portability limitation. The third phase is orchestration planning whereby the workloads are mapped to providers and sequences of execution determined. Adaptive execution is the fourth stage in which the control of provisioning, the schedule of migration, rollback controls and security enforcement are put in place during transition. The fifth phase is the post-migration optimization which entails scaling, re-placement, monitoring, cost refinement, and drift response. This staged reading aligns the migration literature with orchestration and resource-management studies that might otherwise appear disconnected.

Early cloud-migration research relied heavily on frameworks, taxonomies, and decision-support structures. The approaches are also useful since migration programs can hardly be simplified to an optimization variable. It requires the representation of organizational preparedness, constraints of governance, legal jurisdiction, data gravity and criticality of service before proceeding to optimization can commence [1-2,5]. The reason why knowledge-based techniques like goal- obstacle modelling is particularly handy at this level is due to the fact that migration programs often have silent blockers which could eventually result in cost overruns, delays, security failures [8]. The main advantage of these approaches is their interpretability and the fact that they are suitable in early planning. Weak support of dynamic adaptation after migration implementation starts is their weakness. It is possible to explain what matters using a set of static frameworks, yet the allocation of different allocations will be poorly determined using these frameworks under varying cloud conditions.

The next important methodological family is the optimization-based brokerage methods. Deployment plans or provider rankings under cost, service-quality, and policy constraints are often determined with the help of mixed-integer programming, integer programming, decomposition methods, and weighted scoring models [10-15]. These methods remain relevant because migration is still constrained by hard factors: data residency, location availability, inter service latency tolerance, service catalog mismatch, provider quotas, and migration sequencing dependencies. When the establishment of a formalization of the problem is possible and when the input parameters do not change that much, optimization-based approaches are appealing. Their key assets are transparency and constraint rigor. Their weaknesses become apparent when environments are highly dynamic, monitoring streams are noisy, or the state space is too large for real-time optimization. Those were actually the kind of conditions that multi-cloud migration programs will face, and that is why AI-driven orchestration becomes a trend.

Learning-based orchestration approaches become especially important when static optimization is too rigid for dynamic environments. Bayesian learning helps in proactive provisioning which approximates future resource requirements based on what has been previously observed [16]. The wider machine-based research on resource management structures the area into workload prediction, provisioning, placement, consolidation, and scheduling of tasks demonstrating that AI systems can be helpful at various cloud-control levels [17-18]. Deep reinforcement learning extends this line of work by learning placement and scheduling rules through interaction with the environment, a fact that is particularly handy in case choice objectives are multidimensional or partially observable [19]. Multi agent reinforcement learning introduces additional considerations to distributed cloud environments as placement and reallocation choices could be disseminated throughout interacting controllers [21]. The primary benefit of these

strategies is flexibility in adverse conditions. A major weakness is explainability: orchestration decisions may be difficult to audit, particularly when stakeholders require justification for decisions involving security sensitivity or high cost.

Security-conscious methodologies remain less mature than cost-conscious ones, although literature is evolving. Migration risk literature gives taxonomies of threats and vulnerabilities [5], whereas secure allocation work presents authentication-conscious mechanisms in the multi-cloud allocation pipelines [20]. The methodological difficulty lies in the fact that security constraints are often treated qualitatively in planning but quantitatively at runtime, creating a disconnect between governance intent and orchestration action. An effective and affordable migration strategy must thus have a consolidated representation that policy, trust, risk, and financial characteristics can be accessed by the same decision maker. Without such integration, orchestration may reduce cost while violating governance assumptions or strengthen controls while generating financial inefficiency. AI-directed orchestration is most appropriate when it involves predictive ability and clear policy limits as opposed to uninhibited maximization.

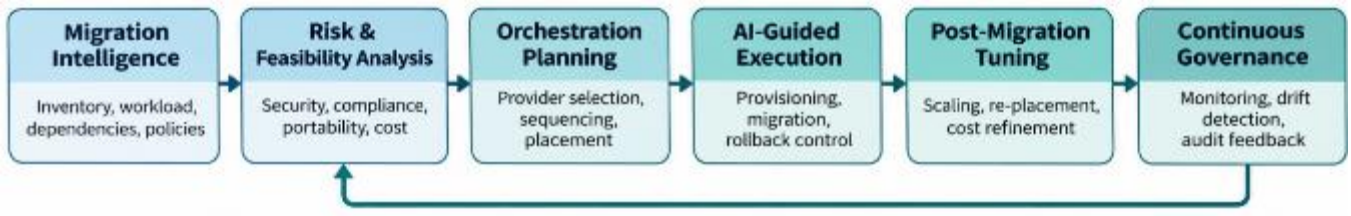


Figure 1: Conceptual framework

The core decision stages, as they are discovered in the literature, are depicted in Figure 1; the workload and policy discovery comes first, and the post-migration adaptation comes last. The figure shows that AI-guided orchestration is not a single-layer model, but a management system that links assessment, optimization, execution, and feedback within a security- and cost-aware framework.

A final methodological pattern worth highlighting is the shift from treating migration as project management to treating it as continuous orchestration. The existing research on resource-allocation-as-a-service with various cloud providers suggests that allocation itself can be open as a reusable decision layer [22]. The implications of that thought on migration are significant: rather than writing placement decisions into the design workshop, organizations can make secure and cost-conscious allocation a control service invoked on an ongoing basis. This transition will probably characterize the next stage of studies in multi-cloud migration as it puts the architectural modernization of systems in line with the dynamic operations instead of dividing the transition and the steady-state management.

4 DISCUSSION

The reviewed studies suggest that the value of AI-guided orchestration lies in its ability to balance interacting factors that are often considered separately in traditional migration planning. In multi-cloud migration, cost, risk, performance, and governance are tightly coupled. It was shown in database migration evaluation research, that workload-informed models are able to approximate the migration duration, migration cost, as well as the future running cost, with relative error in the range of 4-22 percent among the real migrations [7]. This finding is notable in the transformation of planning of migration as a subjective estimation to scenario analysis which can be quantified. It also states that predictive migration tool can significantly decrease the uncertainty in decisions before one starts executing. However, the same line of research also reveals an important limitation: the credibility of these models requires appropriate workload and schema characterization. The quality of orchestration will be poor even with sophisticated downstream algorithms due to poor visibility in the source environment.

An alternative set of results is found in the literature on migration risk. Risk-analysis research indicates that information-security and data-access risks receive the greatest emphasis in cloud migration, whereas compliance, financial, and managerial risks appear less dominant in the reviewed corpus [5]. These results prove the thesis that secures migration is not a marginal issue. It is a major consideration in orchestration design since exposure to risks influences the choice of the provider, sequencing, identity architecture, and data-movement controls. What this means to AI-directed orchestration is that cost minimizing placement does not internalize the risk types and will therefore be trying to maximize the incorrect criterion. Security-conscious orchestration should hence not view risk as an external linkage, but rather an input variable.

This interpretation has been reinforced by findings on brokerage and placement research. earlier multi-provider placement research stated that optimized brokering may be more beneficial than single-cloud deployment in cost and performance [11]. The work scheduling across several clouds also demonstrated that quality of deployment is highly

dependent on the nature of scheduling strategy that is chosen [10]. Application-based brokering introduced greater formalism through mixed-integer programming and decomposition to come up with optimal deployment plans based on service, jurisdictional, and logical constraints [12]. Subsequent hybrid-brokering studies reported quantified gains, including up to 7.06% reduction in monetary cost, up to 17.39% improvement in response time, and up to 31.35% improvement in data-centre processing time [13]. Such reported gains are analytically significant since the operation of migrating into multi-cloud spaces without the quality of brokering could merely duplicate suboptimal placement under increased complexity of operations. According to the literature, orchestration quality directly conditions the financial case for multi-cloud adoption.

The current research also shows a limitation that is common to service-broker research. Existing reviews of cloud service brokers show that service selection remains difficult because provider offerings vary in interfaces, metrics, granularity, and evaluation assumptions [14]. Even incorporated weighting methods with the selection brokers are helpful, however, they rely on the quality and comparability of the input to a large degree [15]. This matters for migration programs because multi-cloud adoption is often pursued in the hope of improving choice quality, yet excessive heterogeneity can instead degrade decision quality rather than enhance it. To overcome this, AI-informed orchestration is at least partially involved in learning the observed patterns of workload and costs, although not the inherent semantic discrepancies between provider catalogs. This leads to the fact that clever orchestration optimizes the decisions on placement at the condition of the metadata and policy abstractions consumed by the orchestration layer being credible and normalized adequately.

The studies on learning-based provisioning posit that adaptive strategies apply particularly once the first migration wave is completed. Research on Bayesian provisioning revealed that predictive resource management is able to enhance a proactive approach to decision-making in cloud applications that are service-based [16]. ML-centric reviews further document the expanding range of cloud resource-management tasks addressed through machine learning, as workload prediction, provisioning, VM location, consolidation, and thermal/energy optimization [17]. Reviews of machine-learning approaches in hybrid cloud models extended that perspective with orchestration being placed in cloud-edge and distributed environments [18]. All these studies suggest that the issue of multi-cloud migration is not completed upon successful migration. The destination environment itself is even a dynamical control problem, and cost optimization is more and more the focus of learning the behavior of migrated workloads under actual usage as opposed to classical assumptions of pre-migration behavior.

The same is added in depth by learning research. Recent reviews suggest that DRL-based scheduling techniques have strong potential, and that the problem of cloud scheduling can be addressed directly due to its large state space, uncertainty in treatment goals, and dynamic workload variability [19]. There are also multi-agent reinforcement-learning allocation models that show that decentralized or semi-decentralized control is attractive in situations where resources have to be released and distributed in a changing demand [21]. These findings align closely with the realities of multi-cloud migration, where workload relocation, backup paths, traffic redirection, and post-cutover scaling create a highly nonlinear operating environment. The primary warning of the analysis is the explainability and governance. Deterministic migration processes in controlled industries can be optimized, but often migration programs have clear audit requirements as to why a workload was relocated, why a provider was chosen, or why a sensitive security-related job was centralized or fractured. Studies reported are more convincing with regard to operational flexibility rather than transparency of decisions.

Orchestration results that are security-conscious are rather sparse and yet informative. Adaptive authentication of secure multi-cloud allocation registered efficiency of 99.09% and security of 98.72% of proposed model [20]. Despite the limitations of evaluation context, the study is helpful since it does not externalize security as an external control but incorporates authentication into the allocation pipeline. This design trend is important in migration programs where temporary trust boundaries are changed as the data flows and service cutover move. A security architecture applied only after placement decisions are made may introduce temporary weaknesses that remain unaddressed. Secure orchestration can thus be best found when control logic, provider selection and enforcement of trust are integrated within the same allocation process.

The literature also indicates the conceptual separation of migration intelligence and runtime orchestration should not be made. All of these approaches operate across different time horizons yet share the same overarching aim: to reduce uncertainty without compromising performance or governance: knowledge-reuse techniques [8], workload-model estimation techniques [7], cost modelling techniques [12], broker-assisted selection techniques [14-15], predictive provisioning techniques [16] and DRL-based scheduling techniques [19]. The current research base has a significant weakness of end-to-end integration across the horizons. Most of the papers optimize isolated phases, but actual migration programs need a feedback mechanism that ties together pre-migration evaluation with real-time adjustment and the post-migration audit. Only in a case where such feedback is clear can AI-directed orchestration be considered strategically beneficial. Otherwise, migration programs risk relying on sophisticated analytics before cutover and simplistic control logic afterward.

Table 2: Method comparison

Ref	Method	Strengths	Limitations
[7]	Workload-model-based migration simulation	Supports prediction of migration duration, migration cost, and running cost from workload evidence	Depends on accurate logs, schema visibility, and model fidelity
[12]	Mixed-integer programming with Bender's decomposition for brokering	Handles multiple constraints including location, service quality, and legal requirements while minimizing deployment cost	Requires formalized inputs and becomes harder to adapt in volatile environments
[13]	Hybrid normalized service brokering with load balancing	Improves cost and performance metrics simultaneously in multi-cloud allocation scenarios	Evaluation remains broker-centric and less focused on migration-stage uncertainty
[15]	Integrated-weighting broker model for service selection	Supports multi-criteria comparison across heterogeneous offerings	Sensitive to weighting assumptions and provider-metadata comparability
[16]	Bayesian learning for dynamic provisioning	Enables proactive rather than purely reactive allocation decisions	Strongly dependent on historical workload behaviour and model assumptions
[19]	Deep reinforcement learning for cloud scheduling	Adapts to dynamic conditions and complex objective spaces	Limited explainability and potentially unstable training behaviour
[20]	Secure allocation with adaptive authentication	Embeds security logic into orchestration decisions rather than adding security afterward	Evaluation scope is narrower than full enterprise migration scenarios
[22]	Resource Allocation as a Service across multiple providers	Treats allocation as a reusable cross-provider decision layer with SLA relevance	Requires strong abstraction and interoperability support across providers

Table 3 shows that reported outcomes are encouraging, but not directly comparable across studies because evaluation environments, workloads, and optimization goals differ substantially. That observation is itself important: the field still lacks uniform evaluation guidelines by which secure, cost-conscious, and AI-guided orchestration strategies in multi-cloud settings can be compared objectively.

Table 3: Results comparison

Ref	System	Metric	Outcome
[5]	Cloud migration risk review model	Dominant risk weight	Information security risk identified as the largest category at 25%
[7]	Workload-model-based database migration evaluator	Relative prediction error	Reported error range of 4%–22% across real migration cases
[11]	Multi-provider VM placement broker	Cost/performance comparison	Multi-cloud placement reported as better than single-cloud deployment on both dimensions
[13]	Hybrid multi-cloud service broker	Monetary cost improvement	Up to 7.06% reduction
[13]	Hybrid multi-cloud service broker	Response-time improvement	Up to 17.39% improvement
[13]	Hybrid multi-cloud service broker	Data-centre processing-time improvement	Up to 31.35% improvement

[20]	Secure multi-cloud allocation framework	Efficiency	99.09%
[20]	Secure multi-cloud allocation framework	Security	98.72%

Figure 2 demonstrates the visualization of a number of quantitative results reported in the reviewed studies. It is a deliberate comparison, not benchmarking graph, since the underlying measurements are not homogeneous: it aims at demonstrating the range of reported measurable gains and risks, as reported in the cost-aware, predictive, and security-conscious orchestration work.

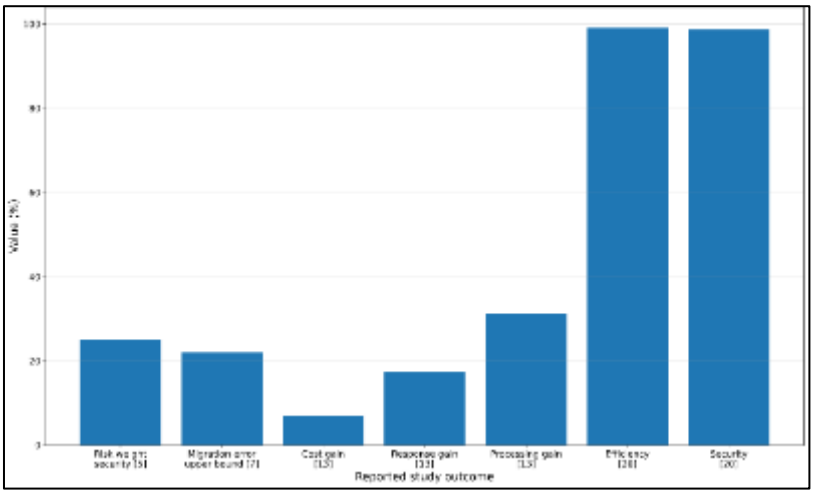


Figure 2: Representative quantitative outcomes reported in selected orchestration studies

Figure 3 visualizes the relationship between the visibility of migration, provider heterogeneity, AI decision rationale, policy enforcement and business outcomes. It accounts for and lends credence to the main thesis of this review by demonstrating that the phenomenon of secure and cost-effective migration occurs due to the combination of interconnected control destinations and not due to individualized algorithmic enhancement.

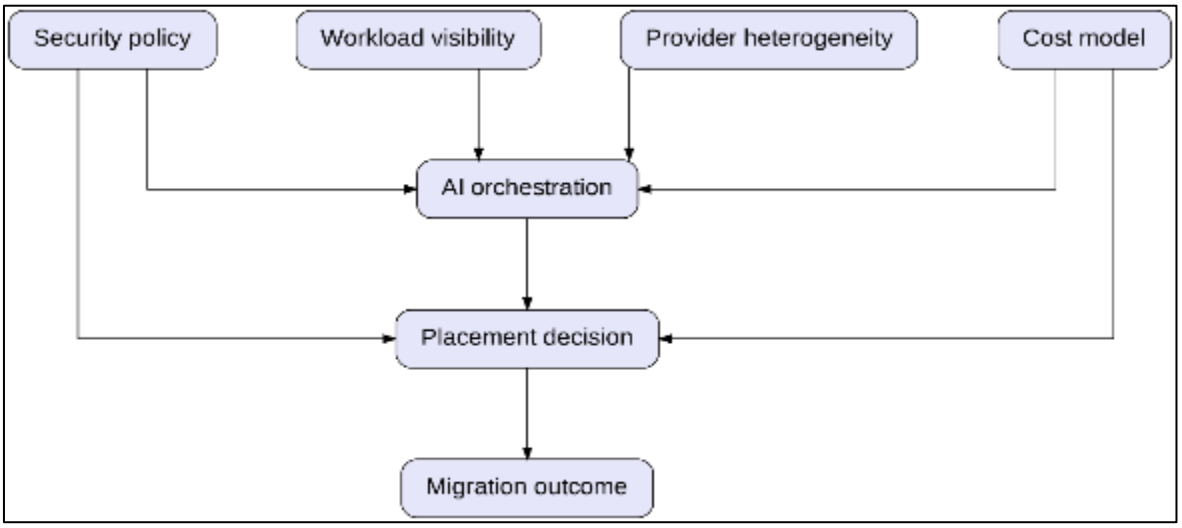


Figure 3: Relationship diagram among security, cost, and orchestration intelligence in multi-cloud migration

Figure 4 synthesizes the results of the review into the end-to-end model that relates migration assessment, orchestration choice, runtime learning, security enforcement, and financial governance. The figure puts special emphasis on feedback, since fixed migration plans degrade rapidly when workloads start being subjected to actual demand, a shift in provider policies, or post-cutover drift.

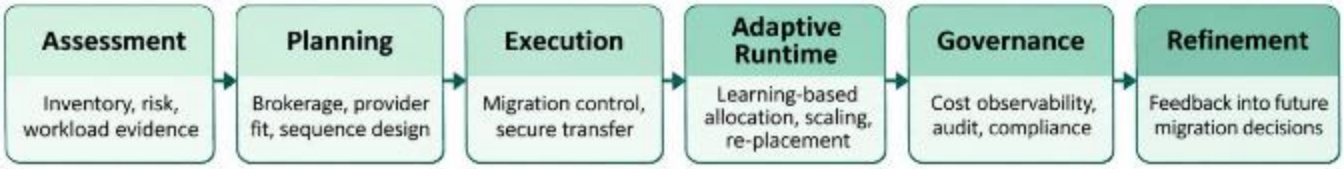


Figure 4: Integrated model for AI-guided secure and cost-aware multi-cloud migration

Future Directions

Future research should focus on orchestration systems that integrate migration-phase reasoning with runtime control. Studies to date tend to give preference to, optimize, or secure the position of the provider or the distribution of work or learning-based scheduling. Continuity across those layers is, however, necessary in the enterprise migration programs. The research agendas should be fronted towards orchestration architectures that preserve migration intent, policy metadata, and workload evidence following cutover, and not throwing them away upon the initial move of the workload. This continuity would ensure that post-migration optimization remains aligned with the goals that justified migration in the first place.

The second priority is related to explainable and auditable AI. Deep learning and reinforcement learning are increasingly viewed as attractive for cloud scheduling and resource allocation [17]–[19], [21], but the migration choices can involve stakeholder review on many occasions, regulatory liability, and forensic traceability. Explanation layers which bridge placement decisions and workload characteristics, cost models, and policy regulations should therefore be included in future orchestration engines. Explainability is especially important in industries where provider choice, data location, or service-dependency mapping carries legal consequences. The orchestration research of the next generation must consider interpretability as an operational requirement and not a visualization option.

The third avenue of research is greater security integration. Migration risk taxonomies are established well [5]; however, numerous security-indirect orchestration approaches continue to be used. Next-generation systems should support policy-native allocation in which encryption requirements, key-control boundaries, identity-trust levels, regional constraints, and data-sensitivity scores directly constrain orchestration options. Interdisciplinary collaboration between cloud orchestration and formal policy verification could also be used in this direction, as well as zero-trust architecture and runtime compliance analytics. The initial step is secure multi-cloud allocation studies, but larger enterprise validation should still be conducted [20].

The fourth direction is the direction of cost realism. Cloud-cost optimization is becoming more sophisticated, particularly through graph-based modelling and multi-provider allocation analysis [9], [12], [22]. Nonetheless, numerous studies continue to prioritize infrastructure measures and minimize observability cost, egress volatility, license impact, security tooling overhead, and operating cost in organizations. The cost must be used as a stratified and changing temporary variable in future work. Modelling of how AI can orchestrate will be much more practical once the cost models consider realistic migration programs as opposed to simplistic infrastructure scenarios. This kind of work would go a long way in enhancing the business cases of cloud migrations.

Finally, empirical assessment should also be enhanced. Cross-provider testing is still scarce, and most of the evidence stems either through simulation, developed benchmarks, or small provider sets. Future studies require open multi-cloud testbeds, richer migration traces, and standardized evaluation protocols that assess cost, security, performance, rollback resilience, and policy compliance within the same experimental setting. In the absence of stronger empirical comparability, the discipline will remain able to make valuable local innovation, but it will not be able to find out broadly transferable orchestration directions capable of making secure and cost-optimized migration on an enterprise scale.

5 CONCLUSION

The complexity of secure and cost-efficient multi-cloud migration has made AI-guided orchestration increasingly necessary. The literature shows that migration success depends on far more than destination selection alone. It is based on the representation and coordination of workload evidence, the heterogeneity of providers, risk-type, security control, and financial model representation during the migration lifecycle. Early migration reviews clarified the structural and quality-related issues of cloud transition [1], [6], while orchestration and brokerage studies showed that deployment quality under multi-provider constraints is strongly conditioned by resource-selection and service-brokering logic [4], [10]–[15]. This was then followed by machine-learning oriented studies demonstrating how adaptive provisioning, predictive control and reinforcement learning based scheduling can enhance orchestration in the presence of dynamic conditions [16-19,21].

Several insights stand out. First, migration planning, runtime orchestration, and post-migration optimization should be treated as a single continuum of control problems rather than as discrete project phases. Second, secure orchestration is most effective when policy and trust constraints are embedded in allocation logic rather than added afterward. Third, it is impossible to optimize costs in a multi-cloud environment by mere price comparison, but it is necessary to have structural model of dependencies and overheads. Fourth, AI techniques are most effective when supported by strong visibility, normalized metadata, and governance-conscious constraints. In the absence of such foundations, intelligent orchestration may automate weak assumptions and produce unreliable, inefficient, or non-compliant decisions.

Significant research gaps remain. Important gaps remain in explainability, cross-provider empirical validation, post-migration drift management, and integrated evaluation of security, cost, and performance. Nevertheless, the analyzed literature shows the manifestation of a definite trend: multi-cloud migration tends towards adaptive, evidence-based, and policy-conscious orchestration. Further progress will depend on hybrid techniques that combine formal optimization, predictive analytics, learning-based adaptation, and explicit governance controls within a single migration operating model.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The author declares no conflict of interest.

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