



Review

Lung Allograft Size Matching in Transplantation: From Global Metrics to Imaging-Based Approaches

Tony Boualoy ^{1,2,†} , Dhiaeddine Djabri ^{1,2,†}, Ahmed H. Aly ^{1,3}, Ammu V. Alvarez ¹ , Matthew C. Henn ¹, Bryan A. Whitson ^{1,2}, Peter J. Kneuert ³ , Yuan Xue ⁴, Doug A. Gouchoe ^{1,2,3} and Kukbin Choi ^{1,*}

¹ Division of Cardiac Surgery, The Ohio State University Medical Center, N-825 University Hospital—Doan Hall, 410 W. 10th Ave., Columbus, OH 43210, USA; tony.boualoy@osumc.edu (T.B.); dhiaeddine.djabri@osumc.edu (D.D.); matthew.henn@osumc.edu (M.C.H.)

² COPPER Laboratory, The Ohio State University Medical Center, 400 W. 12th Ave., Columbus, OH 43210, USA

³ Division of Thoracic Surgery, The Ohio State University Medical Center, N846 Doan Hall, 410 W 10th Ave., Columbus, OH 43210, USA

⁴ Department of Biomedical Informatics, College of Medicine, The Ohio State University, Columbus, OH 43210, USA

* Correspondence: kukbin.choi@osumc.edu

† These authors contributed equally to this work.

Abstract

Accurate donor–recipient allograft size matching remains a critical determinant of outcomes in lung transplantation, yet current approaches rely predominantly on predicted total lung capacity (pTLC) and height-based metrics derived from population-based equations. These simplified surrogates fail to capture individual anatomical variability, disease-specific alterations in thoracic geometry, and the spatial relationship between donor lungs and recipient chest cavities. In this review, we examine the limitations of conventional size matching and synthesize emerging evidence supporting imaging-based approaches, including computed tomography (CT) volumetry, radiomics, and machine learning. CT-derived volumetric analysis enables individualized anatomical assessment and has been associated with clinically relevant prediction of primary graft dysfunction and mortality. Advanced computational methods may further support the extraction of imaging-derived features and integration with clinical data, although these approaches remain investigational. Collectively, these developments signal a paradigm shift from crude population-based metrics toward imaging-driven and computational approaches in the modern era. With rigorous validation and careful clinical integration, imaging-based approaches may complement conventional size metrics and support more individualized donor–recipient assessment.

Keywords: lung transplantation; size matching; CT volumetry; AI and machine learning; segmentation; outcomes



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1. Introduction

Lung transplantation remains the definitive therapy for patients with end-stage pulmonary disease [1,2]. However, the limited availability of donor lungs remains a major barrier, with waitlist demand continuing to outpace organ availability [3,4]. This constraint underscores the need to use each donor organ effectively while maintaining acceptable post-transplant outcomes. A key modifiable factor is donor–recipient allograft size matching, as mismatch introduces physiologic strain that adversely affects both perioperative outcomes and long-term survival [5]. Early size-matching strategies relied on simple measures such

as donor–recipient height differences [6,7]. This approach offered a simple and pragmatic means of approximating donor–recipient size; however, it is a crude surrogate that fails to reliably match donor and recipient size [7]. Given these limitations, size matching subsequently evolved to using predicted total lung capacity (pTLC) [6,7]. pTLC is typically calculated using European Respiratory Society reference equations: $7.99 \times \text{Height (m)} - 7.08$ for males and $6.60 \times \text{Height (m)} - 5.79$ for females, with size matching expressed as pTLC ratio, defined as the ratio between donor and recipient pTLC [8]. Recipients are commonly classified as undersized, size-matched, or oversized based on pTLC ratio thresholds [9,10]. While this provides a practical method for estimating lung volumes in both donors and recipients, these formulas are population-derived, do not reflect true chest cavity size, and are often unreliable in cases of chronic lung disease [11,12].

The relationship between size mismatch and transplant outcomes is disease-specific, with both undersizing and oversizing associated with adverse outcomes depending on the underlying pathology [13,14]. Undersizing results in increased mechanical stress and overdistension of smaller grafts within a relatively larger thoracic space [5,15]. This has been linked to increased perioperative morbidity, including primary graft dysfunction (PGD), prolonged mechanical ventilation, airway complications, and longer hospital length of stay [15]. Conversely, oversizing may impair chest wall mechanics, limit graft expansion, and increase intrathoracic pressures, potentially contributing to complications such as PGD and the need for delayed chest closure or graft reduction. The impact of oversizing has been associated with increased rates of PGD, higher perioperative mortality, and worse long-term survival [16,17]. These limitations are particularly important in the setting of limited donor organ availability and underscore the need for more accurate approaches to donor–recipient size matching to optimize outcomes for each transplanted allograft.

Novel approaches to lung size matching have emerged to address these limitations. Advances in imaging have enabled the use of computed tomography (CT) derived volumetry to directly quantify lung volume and thoracic dimensions, providing a patient-specific assessment of donor–recipient compatibility [11,12]. Unlike pTLC-based estimates, CT volumetry reflects true anatomic constraints and may better capture donor–recipient allograft size matching [12]. Additionally, CT volumetry combined with emerging artificial intelligence (AI)-based models may offer a more precise, data-driven approach to donor–recipient size matching by directly assessing lung volume and thoracic constraints. Although AI and machine learning (ML) have been increasingly explored across transplantation, relatively little attention has been devoted to donor–recipient size matching in lung transplantation. Furthermore, existing discussions often address imaging, radiomics, and predictive modeling separately rather than as complementary components of a precision size-matching framework. This review synthesizes current evidence on conventional lung sizing strategies, their limitations, and emerging imaging-based and AI-driven approaches, with a focus on donor–recipient size matching in lung transplantation.

2. Literature Search Strategy

This narrative review was informed primarily by literature identified through PubMed searches conducted through June 2026. Searches were performed using combinations of the terms “lung transplantation,” “size matching,” “predicted total lung capacity,” “CT volumetry,” “radiomics,” “machine learning,” “artificial intelligence,” and “donor–recipient compatibility.” Priority was given to landmark studies, contemporary investigations, and clinically relevant reviews addressing donor–recipient size matching and emerging imaging-based approaches in lung transplantation. Reference lists of selected articles were also reviewed to identify additional relevant publications, and targeted supplementary literature searches were performed when necessary to identify recently published peer-reviewed

articles not yet indexed in PubMed. Only English-language articles were included. Peer-reviewed journal articles and selected conference abstracts were considered, whereas preprints were not included.

3. Clinical Consequences of Size Mismatch

Size mismatch in lung transplantation has broad clinical implications, affecting not only graft function but also perioperative morbidity, resource utilization, and long-term outcomes [14–16]. The clinical impact varies by direction, degree of mismatch, and underlying disease. PGD is one of the most immediate and clinically significant complications following lung transplantation, occurring in 15–25% of recipients and strongly associated with increased ICU length of stay and both 90-day and 1-year mortality [16,18,19]. Size mismatch imposes mechanical and physiologic stress on the transplanted lung, increasing susceptibility to early graft dysfunction. Excessive mismatch may influence PGD risk in both directions, with prior studies reporting increased risk among recipients of both undersized and oversized allografts [5,16,20,21]. Beyond early graft injury, size mismatch has additional important post-transplant implications. Undersizing has been associated with increased airway complications, including airway dehiscence and higher tracheostomy rates, while larger degrees of mismatch have been linked to increased risk of chronic lung allograft dysfunction (CLAD) and reduced long-term survival [6,15,20]. Notably, size discrepancies greater than 20% have emerged as independent predictors of the composite outcome of CLAD and mortality, underscoring the importance of appropriate donor–recipient matching [14,20].

The mechanisms underlying these complications differ depending on the direction of mismatch, in addition to specific disease processes. Undersizing results in increased mechanical stress and overdistension of smaller grafts within a relatively larger thoracic space, contributing to ventilator dependence, airway complications, prolonged recovery, and increased healthcare resource utilization, including longer hospitalizations and higher costs, with index hospitalization charges approximately \$18,000 greater in undersized recipients (\$176,247 vs. \$158,492) [5,14]. Conversely, oversizing impairs chest wall mechanics, limits graft expansion, and increases intrathoracic pressures, leading to restricted ventilation, PGD, and the need for delayed chest closure or graft reduction. The clinical impact of mismatch appears most pronounced at greater degrees of discrepancy, where excessive undersizing or oversizing is associated with worse early outcomes and reduced long-term survival [14].

These effects are particularly evident in restrictive lung disease, where both undersizing and excessive oversizing have been associated with increased mortality [15,16]. Emerging data further suggest that CT-based volumetric assessment may better predict complications such as PGD and mortality, highlighting the limitations of traditional size-matching approaches [5]. However, the relationship between early graft injury and long-term outcomes is complex and non-linear. Recent analyses demonstrate that even severe early injury, such as PGD grade 3 (PGD3), may not alone predict long-term survival after adjustment for recipient, donor, and post-transplant factors. Instead, downstream complications, including dialysis and treated rejection, appear to play a more dominant role in determining long-term outcomes among patients who survive the index hospitalization [19]. These findings suggest that the impact of donor–recipient allograft size mismatch on long-term outcomes is indirect and incompletely captured by conventional global metrics, which do not account for the complex, multifactorial pathways linking early physiologic stress to long-term survival.

4. Disease-Specific Complexity

The clinical impact of size mismatch varies with underlying disease [17,22]. A central limitation of current approaches is that pTLC-based sizing does not account for true thoracic dimensions, which vary substantially across disease states [11]. Patients with chronic obstructive pulmonary disease (COPD) typically have hyperinflated lungs within expanded thoracic cavities, whereas those with pulmonary fibrosis and other restrictive diseases have contracted lungs within a diminished chest cage. These disease-specific patterns of thoracic remodeling are dynamic and may partially reverse following transplantation, highlighting the limitations of static, equation-based estimates. As a result, identical pTLC ratios may have opposing physiologic and clinical implications depending on the underlying diagnosis, underscoring that a uniform approach to size matching is inherently limited [12,13]. Key disease-specific considerations are summarized in Table 1.

Table 1. Disease-Specific Considerations for Donor–Recipient Size Matching in Lung Transplantation.

Disease Group	Undersizing	Oversizing	Known Risks/Considerations	Related Evidence
COPD/emphysema	Often tolerated, but excessive undersizing may increase ventilatory demand	Often tolerated or potentially beneficial since hyperinflated thoracic cavities may accommodate larger grafts	Oversizing may reduce residual pleural space mismatch, but excessive size discrepancy can still impair mechanics	Eberlein et al. (2012) [5]; Barnard et al. (2013) [9]
Restrictive lung disease/Idiopathic pulmonary fibrosis	Poorly tolerated; associated with increased mechanical stress and adverse outcomes	Narrower tolerance; excessive oversizing may impair chest closure, graft expansion, and chest wall mechanics	Reduced thoracic compliance and remodeled chest cavity make both under- and oversizing clinically relevant	Ganapathi et al. (2017) [15]; Riddel et al. (2021) [14]; Franz et al. (2024) [16]; Prabhu et al. (2024) [12];
Cystic fibrosis/bronchiectasis	Evidence less definitive	Evidence less definitive	Limited disease-specific data available; donor–recipient compatibility should be individualized based on thoracic anatomy and clinical context	Barnard et al. (2013) [9]
Mixed recipient populations	Variable	Variable	Disease-specific anatomy, chest wall remodeling, and surgical constraints should guide interpretation of pTLC ratios	Ouwens et al. (2002) [7]; Eberlein et al. (2012) [10]; Poo-Fernández et al. (2025) [20]

In COPD, oversizing is generally well tolerated and may be beneficial. Oversized grafts (pTLC ratio ≥ 1.1) have been associated with improved graft survival, with incremental increases in pTLC ratio linked to reduced early mortality [20]. In contrast, patients with pulmonary fibrosis and other restrictive lung diseases demonstrate the opposite pattern, where oversizing is associated with worse outcomes [12,16]. Oversized grafts in this population have been associated with higher rates of PGD, increased in-hospital mortality, and reduced long-term survival compared with size-matched or undersized grafts. Notably, both undersizing (pTLC < 0.8) and moderate oversizing (pTLC 1.1–1.2) have been associated with increased mortality in restrictive disease, suggesting a narrow optimal range for donor–recipient size matching [16]. Collectively, these findings highlight that the relationship between graft size and outcomes is highly disease-specific and that reliance on pTLC-based metrics alone may fail to capture these critical physiologic differences.

Although no disease-specific target ranges have been formally established or prospectively validated, retrospective studies suggest that modest oversizing is generally well tolerated in COPD, whereas recipients with restrictive lung disease appear to have a narrower optimal range, centered closer to size matching. These observations are derived primarily from retrospective analyses and should be interpreted as general trends rather than formal guideline recommendations. Consistent with these findings, the 2026 American Association for Thoracic Surgery (AATS) Expert Consensus Document recommends a general donor-to-recipient pTLC ratio of 0.8–1.2 while acknowledging important disease-specific considerations [5,9,12,14–16,23].

5. Emergence of CT Volumetry

Conventional approaches to lung size matching rely on simplified anthropometric estimates such as pTLC and height-based ratios. More recently, imaging-based and computational methods have expanded this framework to enable increasingly individualized assessment of donor–recipient compatibility (Table 2). CT volumetry represents a shift away from equation-based estimates toward direct, patient-specific measurement of lung volume [11,12]. This is particularly important, as size matching is fundamentally an anatomic and physiologic problem, yet current approaches rely on equations derived from variables such as height, sex, and age that do not fully capture individual thoracic dimensions or disease-specific alterations in lung mechanics. By incorporating direct assessment of lung volume and thoracic cage dimensions, CT volumetry enables a more precise evaluation of donor–recipient compatibility, particularly as identical pTLC ratios may have markedly different physiologic implications across disease states. Accordingly, CT volumetry may offer improved accuracy compared with pTLC, particularly when accounting for variation in underlying disease [11,12].

Table 2. Evolution of size matching approaches from conventional metrics to data-driven methods.

Approach	Data Utilized	Strengths	Limitations	Clinical Status
pTLC/Height	Anthropometric	Simple; widely available	Poor individualization	Standard
CT volumetry	Imaging	Patient-specific anatomic assessment	Donor imaging limited availability	Emerging
Radiomics	Imaging features	Captures regional heterogeneity	High complexity; limited standardization	Investigational
Machine-Learning Integration	Multimodal (imaging + clinical)	Enables personalized prediction	Requires validation and interpretability	Experimental

These differences are most apparent in disease-specific contexts. Recent studies in patients with restrictive lung disease suggest that CT-derived volumes may more accurately reflect true lung size and thoracic cage dimensions compared with pTLC-based estimates [24]. Regardless of whether sizing is based on height, pTLC, or CT-derived volumes, a mismatch in either direction is associated with adverse outcomes [5,12,16]. Undersizing has been linked to increased risk of PGD, respiratory insufficiency, and mortality, while oversizing has similarly been associated with higher rates of PGD, impaired chest wall mechanics, and worse survival [5,6,15]. These associations have been demonstrated across registry analyses, single-center cohorts, and CT-based studies, particularly in restrictive lung disease populations. Collectively, these findings suggest that the relationship between size mismatch and outcomes is not unidirectional but instead reflects a narrow

optimal window of compatibility that current one-dimensional sizing metrics incompletely capture [11,12].

From a practical standpoint, CT volumetry is increasingly feasible, particularly on the recipient side, because chest CT imaging is commonly obtained during transplant evaluation. Donor CT imaging is also becoming more readily available as donor assessment protocols evolve. Advances in segmentation software allow for increasingly reliable volumetric assessment across a broad range of clinical scenarios. Importantly, early clinical experience suggests that CT-based assessment may provide additional information to support donor selection, including the acceptance of organs that might otherwise be declined based on pTLC estimates alone. As such, CT volumetry has the potential to improve donor–recipient matching and expand the effective donor pool.

Despite these advantages, CT volumetry remains dependent on image acquisition quality, inspiratory phase standardization, and accurate segmentation. Disease-specific factors such as extensive fibrosis, severe emphysema, or bullous remodeling may further affect volumetric measurements, and implementation currently depends on specialized software and image-processing workflows. Rather than replacing conventional size-matching metrics, CT volumetry may be most appropriately used as an adjunctive tool. Anthropometric measures and pTLC ratios can continue to serve as an initial screening approach, whereas CT-derived assessments may provide additional value in cases where donor–recipient compatibility is uncertain or where thoracic anatomy is poorly represented by population-based estimates, such as restrictive lung disease, marked chest wall deformity, prior thoracic surgery, or substantial donor–recipient size discrepancy.

6. Advanced Segmentation and Radiomics

Beyond simple volumetric measurements, advanced image segmentation and radiomic analysis enable the extraction of high-dimensional quantitative features from routine CT imaging, including lobar volumes, pulmonary vessel volume, parenchymal density patterns, and markers of small airway disease [25–27]. These advances enable a transition toward multidimensional characterization of lung structure and function (Figure 1).

Following CT acquisition, segmentation of the lungs, thoracic cavity, or individual lobes enables direct quantification of volumetric measurements and facilitates the extraction of additional imaging biomarkers and radiomic features that may reflect underlying graft quality and physiologic reserve. These measurements form the foundation of an imaging-analysis pipeline in which quantitative imaging features are combined with donor and recipient clinical variables to create structured datasets suitable for predictive modeling. Within this framework, machine learning models can identify complex relationships among imaging and clinical variables that may not be captured using conventional approaches. Rather than relying on a single metric, such as pTLC, these models can estimate donor–recipient compatibility, predict risks of PGD or CLAD, and generate individualized assessments of donor–recipient compatibility and post-transplant risk. Such approaches may support donor acceptance decisions by integrating multiple dimensions of graft suitability into a unified compatibility assessment.

Machine learning-based radiomics has demonstrated superior performance compared to conventional imaging assessment in detecting allograft injury and predicting clinically relevant transplant outcomes. In preclinical models, radiomic analysis has shown markedly improved accuracy for detecting allograft rejection compared to standard uptake value measurements [28]. In clinical lung transplantation, CT-based machine learning tools have successfully quantified features such as ground-glass opacity, reticulation, and pulmonary vessel volume, with the latter emerging as a strong predictor of restrictive allograft syndrome and graft failure [26].

More recently, deep learning approaches have begun to integrate donor lung CT imaging directly into predictive models of transplant outcomes. When combined with clinical data, these models demonstrate improved performance compared to clinical variables alone, highlighting the incremental value of imaging-derived features in risk stratification [29]. Importantly, CT-based machine learning approaches have also been shown to identify structural abnormalities not captured by conventional assessment and to stratify recipients at markedly increased risk of adverse outcomes, including intensive care unit (ICU) stay and chronic lung allograft dysfunction [30]. Together, these findings highlight the subjectivity and limitations of current donor evaluation practices and suggest that imaging-based phenotyping may provide complementary information for risk stratification.

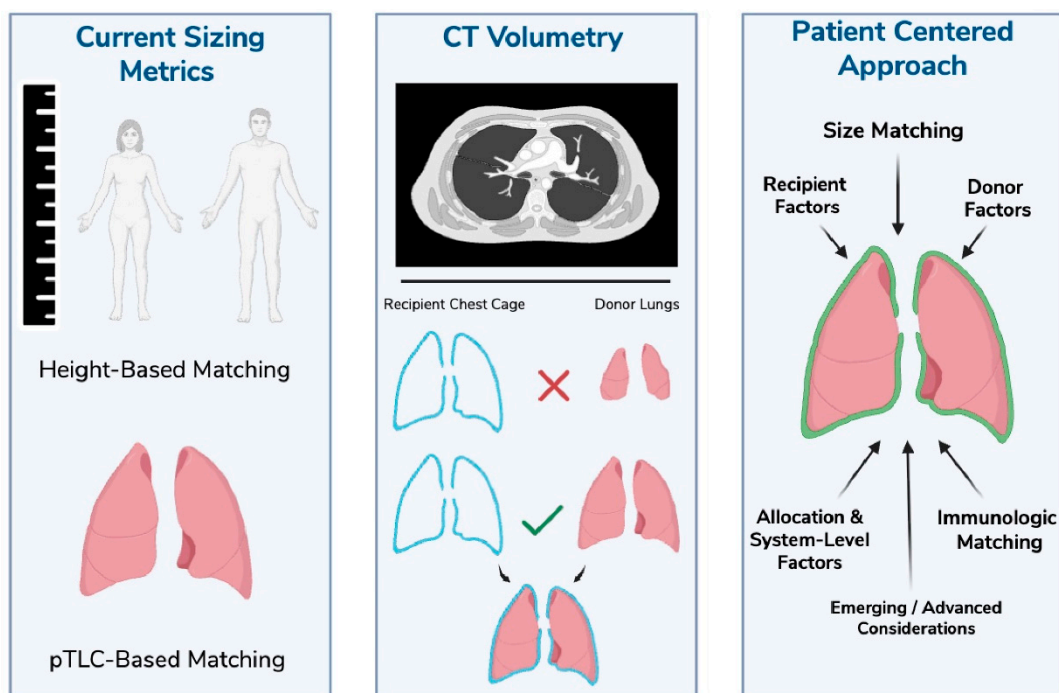


Figure 1. Evolution of donor-recipient lung size matching in lung transplantation. Conventional approaches rely on anthropometric surrogates, such as height and predicted total lung capacity (pTLC). CT volumetry enables direct assessment of donor lung and recipient cavity size, while future patient-centered approaches may integrate anatomic, donor, recipient, immunologic, and allocation-related factors to optimize donor selection.

7. Machine Learning and Artificial Intelligence (AI) Applications

Machine learning and AI offer transformative potential across lung transplantation, particularly in donor–recipient matching and outcome prediction. Recent literature has demonstrated that machine learning approaches, including random forests, support vector machines, and neural networks, consistently outperform traditional statistical methods in modeling complex transplant-related outcomes [31–35]. These approaches may be particularly valuable in transplantation, where outcomes are driven by highly nonlinear interactions between donor, recipient, and procedural factors. In thoracic surgery, machine learning models have demonstrated strong predictive performance for postoperative outcomes following complex procedures such as esophagectomy, with neural networks and ensemble methods showing improved performance over conventional regression approaches [36]. These findings highlight the limitations of traditional models in capturing multifactorial risk, which directly parallels the inadequacy of simplified metrics such as pTLC in donor–recipient size matching.

Importantly, machine learning frameworks enable integration of diverse data types, including clinical variables, imaging features, and emerging molecular markers. For example, random survival forest models have demonstrated superior discrimination and calibration compared to conventional Cox regression in predicting post-transplant survival [37,38]. Similarly, hybrid models incorporating multimodal data have demonstrated reliable predictive performance across short- and long-term outcomes, with good calibration and demonstrated clinical utility in decision curve analyses [39]. Recent work has begun to explore AI-assisted evaluation of donor lung CT imaging for donor assessment and transplant decision-making, further underscoring the rapid emergence of imaging-based approaches [40]. Collectively, these advances underscore the potential of AI-driven approaches to move beyond static, one-dimensional metrics toward more dynamic, personalized models of donor–recipient compatibility.

Despite encouraging early results, most machine learning applications in lung transplantation remain in relatively early stages of development. Many published models are derived from retrospective analyses, single-center cohorts, or modest sample sizes, which may limit generalizability and increase the risk of overfitting. In addition, differences in patient populations, imaging protocols, and clinical practice patterns may affect model performance across institutions. Among currently available approaches, CT-derived volumetric assessment and imaging-based risk prediction models may be the closest to clinical implementation because they leverage routinely acquired imaging and address clinically relevant decision points. However, broader adoption will require multicenter validation, prospective evaluation, standardized data pipelines, and integration into clinical-facing decision-support workflows. Importantly, model interpretability and transparency will be essential to facilitate clinical adoption and effective implementation.

8. Integration of Multi-Modal Data

Building upon the limitations of one-dimensional size metrics, the future of lung size matching likely lies in integrating CT volumetry, radiomic features, and machine learning into unified, multidimensional predictive models. Such approaches enable a shift from simplified global estimates toward more comprehensive assessments of donor–recipient compatibility. AI-driven models may incorporate imaging, clinical variables, and emerging molecular data to improve donor evaluation, organ allocation, and outcome prediction [34].

As an illustrative example, a future decision-support system could integrate conventional pTLC estimates, CT-derived volumetric assessments, radiomic features reflecting parenchymal quality, and machine learning-based predictions of PGD risk. In this framework, a donor–recipient pair initially considered marginal based on pTLC alone might be reclassified as appropriately size-matched or volumetric compatibility, and imaging-derived quality metrics, and predicted post-transplant risk remain favorable. Conversely, unfavorable imaging characteristics or elevated predicted risk could prompt additional scrutiny despite apparently acceptable conventional matching metrics. Such approaches could augment, rather than replace, clinical decision-making during donor acceptance decisions.

Across the transplant continuum, these tools may enable more precise and individualized decision-making. In the pre-transplant phase, machine learning has the potential to enhance donor–recipient matching through objective imaging analysis and risk stratification. Throughout the peri- and post-transplant periods, predictive models could identify patients at risk for complications such as PGD and CLAD, facilitating earlier intervention and personalized management strategies [34,41,42].

Multimodal frameworks may enable the integration of heterogeneous data types, overcoming the limitations of traditional models that rely on isolated parameters. Techniques such as transfer learning could support model development in data-limited settings, while

advances in automated segmentation and feature extraction facilitate scalable implementation of imaging-based analytics [29,35,43].

Multimodal integration enables lung size matching to incorporate complementary dimensions of graft suitability, including regional lung volume distribution, parenchymal quality, vascular architecture, and recipient-specific physiologic demand, and donor-related factors. Future compatibility models may integrate image-derived features with clinical variables such as donation after brain death (DBD) versus donation after circulatory death (DCD), ischemic time, donor quality metrics, and recipient disease phenotype to provide a more comprehensive assessment of donor–recipient compatibility. These approaches may eventually complement conventional size metrics by incorporating additional anatomic and clinical information, although their role in routine donor–recipient matching remains to be defined.

9. Barriers to Clinical Implementation

Despite promising results, several barriers limit the clinical adoption of AI-driven approaches in lung transplantation. These challenges span technical, methodological, and clinical domains (Table 3). From a technical standpoint, the availability and quality of data remain major limitations. Many models are developed using small, single-center datasets with substantial heterogeneity in data acquisition and processing. For CT-based approaches, variability in imaging protocols, the need for standardized segmentation, and reliance on specialized software further complicate implementation [12,24,34,44]. Recent multicenter investigations have demonstrated substantial variability in chest CT imaging quality across scanner platforms and institutions, highlighting a potential source of performance degradation and reduced generalizability when imaging-based models are deployed outside of their developmental environment [45]. Although CT-derived lung volumes can be obtained in most recipients, donor CT imaging is not consistently available across all donor evaluations, often necessitating reliance on predictive equations rather than direct volumetric measurement, which may introduce additional variability [46–48].

Table 3. Key barriers to clinical implementation of AI-driven approaches in lung transplantation.

Domain	Barrier	Example
Technical	Data heterogeneity	CT protocol variability
Methodologic	Lack of validation	Single-center studies
Clinical	Workflow integration	EMR compatibility
Ethical	Bias, consent	Underrepresented populations

Methodologically, limitations in model development and validation hinder generalizability. Many studies lack external validation, use inconsistent performance metrics, and provide limited insight into model interpretability. More broadly, the lack of standardized approaches to model development, reporting, and validation limits comparability and clinical translation [38]. These challenges are further compounded by variability in institutional workflows and differences in resource availability across transplant centers, which may limit the scalability of AI-driven approaches. Broader clinical and ethical considerations present additional obstacles. Issues such as data privacy, regulatory compliance, interoperability across healthcare systems, and algorithmic bias must be addressed to ensure safe and equitable implementation [32,43]. Beyond algorithmic performance, questions surrounding transparency and accountability remain unresolved. Although AI-based tools may assist donor evaluation and matching decisions, final donor acceptance decisions ultimately remain the responsibility of the transplant team. Accordingly, model outputs must

be sufficiently interpretable to support clinician oversight, particularly in the time-sensitive setting of donor evaluation, where decisions are often made under the constraints of cold ischemic time. Centralized donor assessment models, including regional procurement or perfusion centers, may create opportunities for more standardized imaging acquisition and advanced allograft evaluation, but their feasibility, cost, and workflow implications require careful study [49–51]. Collectively, these barriers underscore that despite rapid advances, translating AI-driven lung size matching into routine clinical practice will require not only technical innovation but also rigorous validation, standardization, and thoughtful integration into existing clinical workflows, as AI models must adapt in tandem with ongoing changes in transplant practice.

10. Conclusions

Conventional approaches to lung size matching, based on pTLC and anthropometric ratios, remain fundamentally limited by their reliance on simplified population-based estimates that fail to capture the complex anatomic and physiologic variability underlying graft function after transplantation. These limitations contribute to clinically meaningful size mismatch and are associated with adverse outcomes, particularly in patients with restrictive lung disease. CT volumetry offers a more anatomically grounded assessment of donor–recipient compatibility and represents one of the most immediately translatable advances beyond conventional sizing approaches.

Emerging radiomic and AI-driven approaches may further refine compatibility assessment by incorporating regional lung characteristics, parenchymal features, and recipient-specific physiologic factors. While these technologies hold considerable promise, most remain investigational and require multicenter validation, standardized imaging and segmentation workflows, external testing, and integration into clinically interpretable decision-support frameworks. Unlike prior reviews that broadly examine AI across transplantation, this review highlights donor–recipient size matching as a particularly compelling and clinically actionable application of imaging-based and computational methods. Future efforts should focus on automated and standardized imaging workflows, broader integration of donor CT imaging into donor evaluation, and the development of multimodal compatibility models that incorporate volumetric, radiomic, clinical, and donor-specific data. Such approaches may ultimately enable disease-specific compatibility frameworks that move beyond uniform sizing thresholds toward more personalized, precision-based donor–recipient matching. Continued collaboration among transplant clinicians, imaging scientists, and biomedical informaticians will be essential to translate these approaches into routine clinical practice.

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Abbreviations

AI	Artificial Intelligence
CLAD	Chronic Lung Allograft Dysfunction
COPD	Chronic Obstructive Pulmonary Disease
CT	Computed Tomography
PGD	Primary Graft Dysfunction
pTLC	Predicted Total Lung Capacity

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