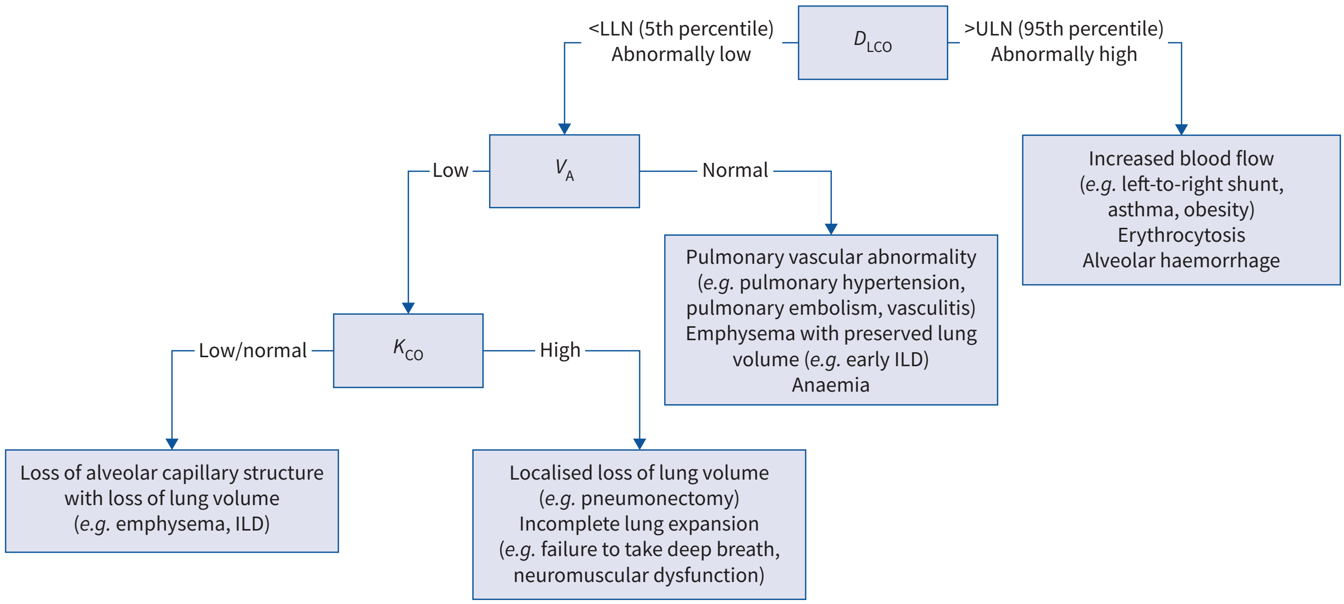

FIGURE 11 Approach to interpretation of diffusing capacity of the lung for carbon monoxide (D_{LCO}). First determine if D_{LCO} is low or high based on the lower and upper bounds defined by the 5th and 95th percentiles of the reference values. A high D_{LCO} is almost always due to increased pulmonary blood volume, as in a left-to-right shunt, increased haemoglobin, as in erythrocytosis, or free haemoglobin in any component of the airway, as in alveolar haemorrhage [180]. To further understand the cause of a low D_{LCO}, next examine its components, alveolar volume (V_A) and transfer coefficient of the lung for carbon monoxide (K_{CO}). If V_A is normal, then this is consistent with pulmonary vascular impairment, emphysema with preserved lung volume or anaemia. If V_A is low and K_{CO} is low or normal, then there is typically loss of alveolar capillary structure such as in emphysema or interstitial lung disease (ILD) with loss of lung volume. If V_A is low and K_{CO} is high, then there is a low lung volume state, either due to localised loss of lung volume, such as from lung resection, which may raise K_{CO} somewhat, or incomplete lung expansion, such as failure to fully inspire, which can increase K_{CO} substantially.

and multidimensional evaluation of lung function and may further improve interpretation. There is also rapid development of wearable devices that allow continuous monitoring of ventilatory indices during daily life (*i.e.* under natural physiological conditions) [169]. Together with applications that capture and interpret data, and integrated enterprise and cloud data repositories, wearable devices will provide novel solutions for personalised respiratory medicine, including tele-monitoring of respiratory function.

In the era of precision medicine and novel prediction tools, more sophisticated diagnostic models should be developed to more accurately identify early determinants of reductions in lung function. Longitudinal data across the life course are essential to identify opportunities for early intervention. There is exciting research in this field that will likely provide significant improvements, especially around the uncertainty of measurements. There are ongoing efforts devoted to the development of AIML approaches to both novel tests as well as currently standard tests. The updated interpretation standards may inform future AIML algorithms and ensure uncertainty is considered in the algorithm. Examples of uses in standard tests include AI analysis of the expiratory flow–volume pattern as noted earlier, along with measurements of inert gas washout and the carbon monoxide measurements through the D_{LCO} exhalation manoeuvre [170]. AIML-based software may also provide more accurate and standardised interpretations, and may serve as a powerful decision support tool to improve clinical practice [171, 172]. AIML may help to develop personalised, unbiased prediction of normal lung function. AIML may enhance the analysis of lung function data by identifying complex, multidimensional patterns associated with disease subtypes. While such algorithms may help to reduce any bias from poor quality data [172], AIML must use only good quality data in training to avoid introducing bias into any algorithms.

The widespread use of electronic health records [173] for data collected during the course of routine clinical practice and large clinical databases from multicentre randomised controlled trials offer unique data sources for training AIML algorithms. These algorithms may be combined with natural language processing, a set of methods which apply linguistics and ML to large corpora of clinical textual passages in order to extract structured information at a large scale. Using linguistics and computer science to process and understand text written in natural language has the potential to extract relevant information on a large