



## Full length article

## Exploring variable observational time windows for patient–ventilator asynchrony during mechanical ventilation treatment

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## ABSTRACT

**Background and Objective:** Patient–ventilator asynchrony (PVA) is prevalent in mechanical ventilation (MV) for critically ill patients and has been associated with adverse patient outcomes. However, studies investigating the associations between PVA and patient outcomes employ differing time windows for PVA evaluation. In this study, machine learning methods are used to quantify the prevalence and magnitude of asynchrony at different time windows, as well as its temporal trends. The study aims to identify the optimal time window for assessing the temporal changes in the asynchrony index (AI) and magnitude of asynchrony ( $M_{asyn,avg}$ ).

**Methods:** This study uses Convolutional Neural Networks (CNN) and Convolutional Autoencoders (CAE) to detect incidences of PVA and quantify its severity in 30 MV respiratory failure patients with 2722 h of respiratory data. The frequency of PVA and the breath-average magnitude were determined over different time periods,  $t$ , where  $t = 0.5, 1, 2, 3, 4, 5, 10, 15, 20, 25, 30, 45, 60$  min and throughout MV. The AI for the patients was determined using the CNN model. Given an asynchronous breath, the CAEs were used to reconstruct asynchrony-free waveforms. The  $M_{asyn,avg}$  was quantified as the difference between the two waveforms. The change in AI ( $\Delta AI$ ) and the change in  $M_{asyn,avg}$  ( $\Delta M_{asyn,avg}$ ) for all time windows,  $t$  were also calculated for each patient.

**Results:** The median [interquartile range] overall AI and  $M_{asyn,avg}$  for the patient cohort are 24.8 [12.9–46.1]% and 37.2 [33.4–45.3]% respectively. Analysis of the patient cohort also shows significant intra-patient variability in AI and  $M_{asyn,avg}$ , while the inter-patient variation in AI is greater as compared to  $M_{asyn,avg}$ . The cohort mean  $\Delta AI$  and  $\Delta M_{asyn,avg}$  exhibit a converging trend with a minima at  $t = 5$  min and with values of  $5.32 \pm 2.37\%$  and  $2.80 \pm 1.03\%$ , respectively. A time window of  $t = 5$  min was preferred for AI and  $M_{asyn,avg}$  evaluation as it can capture the granular changes in asynchrony while also being representative of longer temporal trends, thus preventing excessive variations in patient AI and  $M_{asyn,avg}$ .

**Conclusion:** Overall, this study provides new insight into both the short- and long-term trends of PVA in MV patients. By understanding these patterns, healthcare providers can enhance the monitoring of MV, leading to more informed and timely intervention. Ultimately, this could lead to improved patient care and outcomes.

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## 1. Introduction

Mechanical ventilation (MV) provides life-saving support for critically ill patients with respiratory failure (Major et al., 2018). Recovering patients regain spontaneous breathing effort where

synchronised interactions between the patient and the ventilator are crucial for effective breath initiation, inspiratory flow, and breath termination (Kim et al., 2021; Poor, 2018). Patient–ventilator asynchrony (PVA) occurs when there is a mismatch between the patient’s demand or neural ventilatory pattern with the delivered ventilatory support (De Haro et al., 2018; Mellott et al., 2014; Moorhead et al., 2013). PVA is prevalent in MV patients, with asynchrony manifesting in up to 25%–85% of patient-initiated breaths and has been associated with poor patient outcomes (Blanch et al., 2015; De Haro et al., 2019; Holanda

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**Table 1**  
Summary of findings in studies focused on PVA in MV patients.

No.	Author	Time window	Main findings
1	Loo et al. (2021)	60 min	- The median AI was 32.7% [IQR: 32.1–34.4] per patient. - The median hourly average magnitude of asynchrony, $M_{asyn}$ was 3.8% [IQR: 1.9–4.5] per patient.
2	Souza Leite et al. (2020)	5 min	- 82% of postoperative cardiac patients presented PVA, with an overall AI of 7%. - The most common PVA type was early cycling and double triggering. - Volume controlled (VC) MV group had a higher chance of AI $\geq 10\%$
3	Arunachalam et al. (2020)	Over 10,000 breaths per patient	- In 8 patients undergoing Synchronous intermittent mandatory ventilation (SIMV) VC ventilation, the median AI and $M_{asyn}$ was 80% [50.3–91.8] and 0.8% [0.5–1.3] respectively.
4	Sousa et al. (2020)	Over the duration of MV	- The median AI during the entire period of MV was 5.1% [IQR: 2.6–8.7]. - Median AI was higher in assisted than controlled MV, with 22% of patients having AI $\geq 10\%$ . - Patients with AI $\geq 10\%$ has more extubation failure than patients with AI $\leq 10\%$ .
5	De Haro et al. (2018)	3 min	- Defining clusters of double-triggering (DT) as $\geq 10\%$ DT breaths within 3 min, 59.7% of patients had DT clusters, with a median of 6 cluster events per patient and 41 DT breaths per cluster.
6	Marchuk et al. (2018)	5, 10, 15, 20, 25 min	- Patients tended to remain in the same state (of high or low PVA incidences) even when longer time intervals were considered.
7	Vaporidi et al. (2017)	3 min	- A cluster of ineffective effort (IE) was defined as $\geq 30$ IE's within a 3 min period. - The incidences of IE's in general and $\geq 10\%$ were not correlated with patient outcome. - Clusters of IE were associated with prolonged MV and increased mortality.
8	Ru�� et al. (2017)	Daily (24 h)	- PVAs were positively associated with alive discharge.
9	Rolland-Debord et al. (2017)	12 h	- Severe asynchrony (AI $\geq 10\%$ ) was not associated with alterations of major outcome variables
10	Beitler et al. (2016)	60 min	- The breath stacking (BS) frequency averaged at 27 [7–59] breaths/hour. - Tidal volume ( $V_T$ ) sustained during BS breaths were significantly higher 11.3 [9.7–13.3] mL/kg PBW compared to the preset $V_T$ of 6.3 [6.0–6.8] mL/kg PBW ( $p < 0.001$ ).
11	Blanch et al. (2015)	60 min	- Patients with AI $> 10\%$ had similar rates of re-intubation and tracheostomy with patients of lower AI, but with higher ICU and hospital mortality and a trend towards longer duration of MV.
12	Bryce et al. (2013)	30 min	- Asynchrony may be associated with SIMV with a set respiratory rate $\geq 10$ breaths/min, however not with the duration of MV, mortality or discharge disposition.
13	Costa et al. (2011)	Over the duration of MV	- In a study comparing pressure support and PAV+ MV, 45% of patients (5 of 11) exhibit ineffective efforts (IE) with AI $> 10\%$ , whereas IE was not observed during PAV+. - PAV+ improves patient–ventilator interaction and reduces incidences of end-expiratory asynchrony, and hence reducing AI.
14	Gutierrez et al. (2011)	30 min	- No differences in prevalence of PVA when patients were classified according to MV mode, except for pressure support (PS) MV, where PVA was more prevalent. - PVA prevalence in analysed patient population is $\sim 50\%$ .
15	De Wit et al. (2009)	10 min during first day of MV	- Duration of MV was longer in patients with an IE index $> 10\%$ .
16	Thille et al. (2006)	30 min	- Duration of MV was longer in patients with AI $> 10\%$ . These patients had higher incidences of tracheostomy, although mortality was unaffected.

$M_{asyn}$  – magnitude of asynchrony, PBW – predicted body weight, PAV+ – proportional assist ventilation, IE – ineffective effort.

et al., 2018; Kyo et al., 2021; Souza Leite et al., 2020; Zhang et al., 2020).

Clinically, the asynchrony index (AI) is defined as the number of asynchronous events divided by the total respiratory rate which includes the number of ventilator cycles and wasted efforts (Thille et al., 2006). AI is used to assess patient–ventilator interactions by determining the frequency of asynchronous events within a certain period, however the optimal time period for calculating of AI is not known. Consequently, different studies use different time periods, ranging from 3 min to daily measurements and over the course of MV. Table 1 shows a summary of a few studies with different time windows. Furthermore, the AI provides no measure of the magnitude of asynchrony, which is likely to be an important contributor to the development of injury (Aquino Esperanza et al., 2020; Hashimoto et al., 2023; Zhou et al., 2021). So far, only a few studies have accounted for magnitude to provide more information of patient disease-states, sedation

levels and how patients interact with the ventilator (Ang et al. 2022a; Arunachalam et al., 2020; Kannagara et al., 2016; Loo et al., 2021; Newberry et al., 2016; Sousa et al., 2020). AI has also shows significant intra- and inter-patient variability, warranting continuous real-time monitoring with optimised observational time windows (Blanch et al., 2015; Chao et al., 1997).

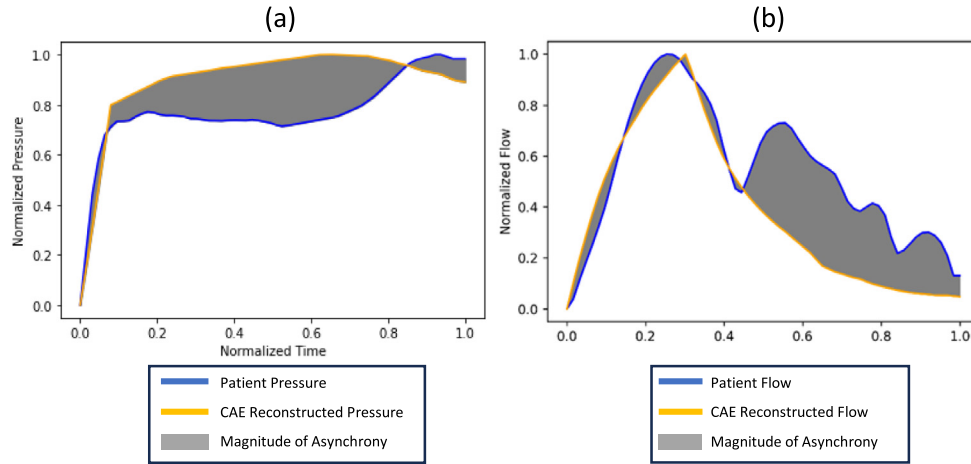
A long observational time window may result in sporadic incidences of PVA being missed, and a brief observation period might not effectively capture instances of PVA that would become apparent during more extended study durations, given that PVA often exhibits episodic or intermittent characteristics (Scott, 2011). In some studies, the observation period is limited and thus unable to capture long-term temporal changes of AI. Therefore, there is a need for long-term monitoring of both the prevalence and magnitude of asynchrony using a suitable time window.

This study investigates 14 different time windows, ranging from 30 s to the entire duration of MV for quantification of AI and

**Table 2**  
Patient cohorts.

Patient cohort	No. of patients	Days of recorded data	No. of recorded breaths	Age (Years) <sup>a</sup>	Weight (kg) <sup>a</sup>	BMI (kg/m <sup>2</sup> ) <sup>a</sup>
CARE <sub>02</sub>	30	200	4,783,264	63.0 [55.0–66.0]	65.0 [60.0–75.0]	25.2 [23.0–28.2]

<sup>a</sup> Age, weight and BMI values are presented as median [interquartile range].



**Fig. 1.** The breath-specific magnitude of asynchrony,  $M_{asyn}$  determined using (a) pressure reconstruction for volume-based ventilation and (b) flow reconstruction for pressure-based ventilation.

asynchrony magnitude using machine learning (ML) approaches based on convolutional neural network (CNN) (Chong et al., 2021) and convolutional autoencoder (CAE) models (Ang, Chiew, Vu, & Cove, 2022; Loo et al., 2021). This range of time windows allows investigation of a suitable time window for asynchrony analysis, while also accounting for patient-specific granular changes in asynchrony. This research also investigates the temporal trend of AI and magnitude of asynchrony in 30 MV patients over 2722 h of respiratory data, providing a longitudinal analysis of asynchrony over an extended period.

## 2. Methodology

### 2.1. Clinical patient data

This study used measured airway pressure and flow data ( $\dot{V}$  data) from 30 retrospective patients from the CARE<sub>02</sub> cohort (ethics approval ref: IUM/504/14/11/2/IREC 2020-100) receiving invasive MV for respiratory failure (Ang, Chiew, Wang, & Nor, 2022c). The demographic of the CARE<sub>02</sub> patient cohort is shown in Table 2. The patients of the CARE<sub>02</sub> cohort were ventilated with various MV modes, where each patient may be ventilated with more than one MV mode throughout the duration of MV treatment. Only respiratory data from the pressure-based MV: pressure control, pressure support, proportional assist ventilation (PAV+) and volume-based MV (volume control) were analysed in this study.

All patients were ventilated using a Puritan Bennett PB980 ventilator (Covidien, Boulder, CO, USA). Airway pressure (cmH<sub>2</sub>O) and flow (L/min) data were recorded at a sampling rate of 50 Hz using a network data acquisition system (Ng et al., 2022, 2021). Individual breathing cycles were processed to remove incomplete breathing cycles. The filtering criteria were defined for each breath in previous works (Ang, Chiew, Wang, et al., 2022; Kim et al., 2019; Lee et al., 2021).

The analysed patient cohort consists of 2722 h of MV data, where 1992 h are pressure-based MV and 730 h are volume-based MV. The patient demographics and length of data for each patient is detailed in Table 3.

### 2.2. Quantification of asynchrony frequency and magnitude

A dual-input CNN was used to classify patient breaths as either an asynchronous or a normal breath (Chong et al., 2021). Data inputs to the dual input CNN model are in the form of one-dimensional structured airway pressure and flow waveforms. The frequency of asynchronous breaths was then used to determine the asynchrony index over varying time windows:

$$\text{Asynchrony Index, AI (\%)} = \frac{\text{Number of asynchronous breaths}}{\text{Total breaths within time window } t} \times 100\% \quad (1)$$

where time window,  $t$  is 30 s, 1 min, 2 min, 3 min, 4 min, 5 min, 10 min, 15 min, 20 min, 25 min, 30 min, 45 min, 60 min and over the entire duration of MV treatment. Furthermore, the magnitude of asynchrony,  $M_{asyn}$  for each breath was also determined using a pressure reconstruction CAE (Loo et al., 2021) for volume-based MV modes and a flow reconstruction CAE (Ang, Chiew, Vu, & Cove, 2022) for pressure-based MV modes. An example of an asynchronous breath, CAE reconstructed breath and the magnitude of asynchrony is shown in Fig. 1 where the magnitude of asynchrony is defined as the difference in area between the asynchronous breath and the CAE reconstructed breath. A breath-average magnitude of PVA,  $M_{asyn,avg}$  was also calculated over varying time windows:

$$\text{Breath average magnitude of asynchrony, } M_{asyn,avg}(\%) = \frac{\text{Breath specific } M_{asyn}}{\text{Total breaths within time window } t} \times 100\% \quad (2)$$

where  $t$  is 30 s, 1 min, 2 min, 3 min, 4 min, 5 min, 10 min, 15 min, 20 min, 25 min, 30 min, 45 min, 60 min and over the entire duration of MV treatment.

### 2.3. Analyses

Both AI and  $M_{asyn,avg}$  were analysed for all 30 patients, using 14 different time intervals, over the duration of MV treatment. The AI and  $M_{asyn,avg}$  calculated using different time windows

**Table 3**  
Patient demographics and hours of MV data for each patient.

Patient	Sex	Age (Years)	BMI (kg/m <sup>2</sup> )	Hours of MV data		
				Pressure-based MV	Volume-based MV	Total
1	M	78	28.0	85	70	156
2	M	62	22.5	133	0	133
3	M	38	21.0	66	125	191
4	M	65	37.0	177	0	177
5	M	55	36.7	52	123	175
6	M	55	23.0	17	18	35
7	F	72	25.3	53	64	118
8	F	61	28.9	127	0	127
9	M	62	20.3	40	9	49
10	M	63	28.2	31	0	31
11	M	36	21.5	80	21	101
12	M	66	24.0	37	25	61
13	M	66	23.9	33	12	46
14	M	66	23.0	0	82	82
15	M	66	25.0	87	0	87
16	M	70	23.4	31	10	41
17	F	50	22.8	36	0	36
18	F	65	23.5	125	5	130
19	M	73	31.3	25	46	71
20	M	69	25.7	130	0	130
21	M	64	25.1	28	22	50
22	F	72	22.0	52	16	68
23	M	62	25.6	102	0	102
24	F	79	28.6	68	0	68
25	M	32	53.3	46	24	70
26	M	37	18.6	66	41	107
27	M	53	30.8	9	15	24
28	M	59	27.1	96	0	96
29	M	58	27.6	58	0	58
30	M	20	88.6	102	0	102
<b>Median</b>	-	<b>63</b>	<b>25.2</b>	<b>56</b>	<b>11</b>	<b>84</b>
<b>[Interquartile Range, IQR]</b>	-	<b>[55–66]</b>	<b>[23.0–28.2]</b>	<b>[34–94]</b>	<b>[0–25]</b>	<b>[52–124]</b>
<b>Total</b>	-	-	-	<b>1992</b>	<b>730</b>	<b>2722</b>

were compared to the values determined using  $t = 60$  min and tested for statistical differences by performing a Wilcoxon ranksum test ( $p < 0.05$ ). Patient-specific cumulative distribution function (CDF) plots and histograms for the  $M_{asyn}$  of all breaths and AI were also plotted. The distributions of  $M_{asyn}$  of all breaths and AI were tested for normality using a Kolmogorov Smirnov test ( $p < 0.05$ ).

In this study, the change in AI ( $\Delta AI$ ) and the change in  $M_{asyn,avg}$  ( $\Delta M_{asyn,avg}$ ) for all time windows,  $t$  were also calculated for each patient. Both metrics were not calculated for  $t =$  entire duration of MV as there would only be a single interval.  $\Delta AI$  and  $\Delta M_{asyn,avg}$  effectively describe the per-interval change in AI and  $M_{asyn,avg}$  respectively as shown in Fig. 2 and the following equations:

$$\Delta AI(\%) = \frac{1}{N} \sum_{n=1}^{n=N-1} |AI_{n+1} - AI_n| \quad (3)$$

$$\Delta M_{asyn,avg}(\%) = \frac{1}{N} \sum_{n=1}^{n=N-1} |M_{asyn,avg,n+1} - M_{asyn,avg,n}| \quad (4)$$

where  $N$  is the total number of intervals (time windows) of duration  $t$ . Normalisation by  $N$  yields the per-interval changes in AI and  $M_{asyn,avg}$ , allowing for inter-patient comparison.

### 3. Results

#### 3.1. Patient AI and $M_{asyn,avg}$

The cumulative distribution function (CDF) plots of the magnitude of asynchrony,  $M_{asyn}$  (all breaths) and AI (using a time window  $t = 30$  s) for 3 patients, namely Patients 2, 4 and 24 are shown in Fig. 3 for illustration purposes. These 3 patients are selected as representation for most of the patient trends.

The median [interquartile range, IQR] asynchrony index (AI) and breath-average magnitude of asynchrony ( $M_{asyn,avg}$ ) using 14 different time windows are presented for each patient in Table A.1 and Table A.2 (Appendix) respectively. The median AI and  $M_{asyn}$  measured over the entire duration of MV and across all patients is 24.8 [12.9–46.1] % and 37.2 [33.4–45.3] %, respectively.

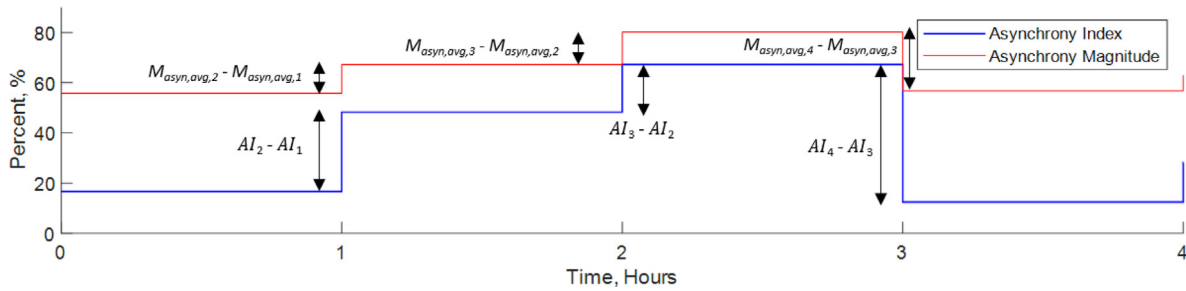
Furthermore, the temporal trend of AI and  $M_{asyn,avg}$  during the first 24 h of MV are presented for 3 patients in Figs. 4 and 6, respectively, using different time windows. For clarity, AI and  $M_{asyn,avg}$  are plotted using time windows of 5, 15, 30 and 60 min. The corresponding histograms for AI and  $M_{asyn,avg}$  of the 3 patients are illustrated in Fig. 5 and Fig. 7. The AI and  $M_{asyn,avg}$  distributions of each patient of the cohort are found to be non-normal (Kolmogorov Smirnov test,  $p < 0.05$ ).

#### 3.2. Investigation of the effect of time window

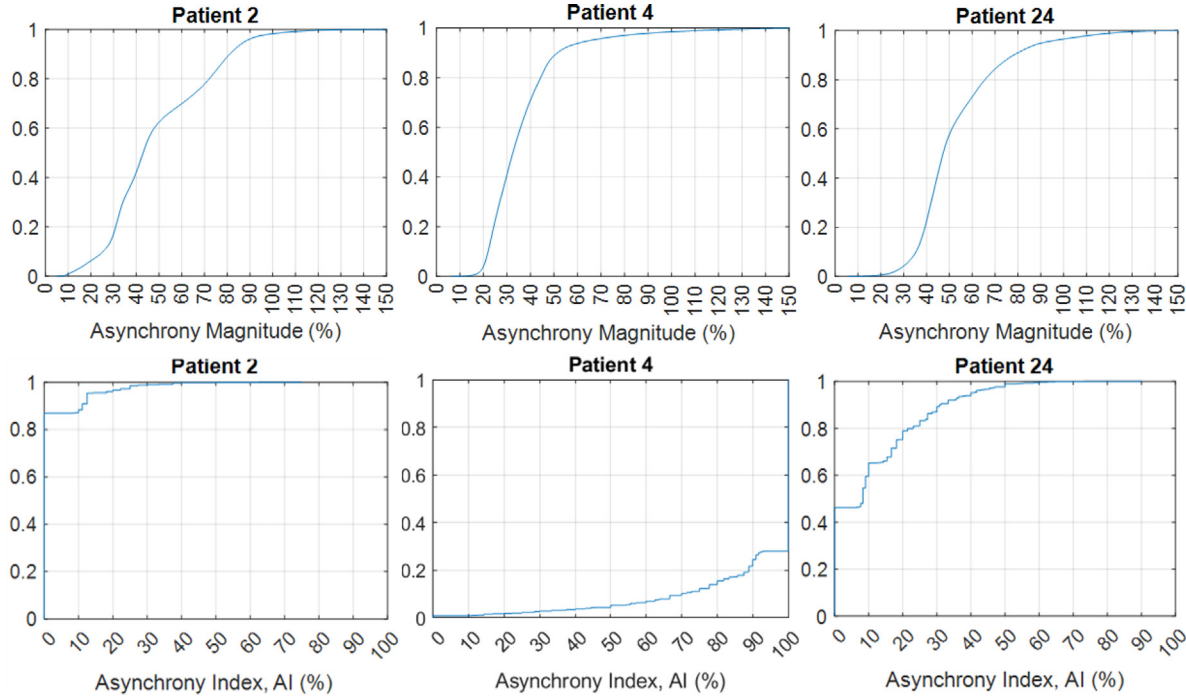
The mean values of  $\Delta AI$  and  $\Delta M_{asyn,avg}$  of the patient cohort are plotted in Fig. 8. The  $\Delta AI$  and  $\Delta M_{asyn,avg}$  calculated for all patients are presented in Tables 4 and 5, respectively. The cohort mean  $\Delta AI$  and  $\Delta M_{asyn,avg}$  was the lowest at 5.32% and 2.80% respectively when using a time window,  $t$  of 5 min.

### 4. Discussion

As shown in Table 3, a total of 2722 h of MV data from a retrospective patient cohort were analysed. Out of the 30 patients analysed, 24 patients were male and 6 were female. A total of 1992 h (73.2%) of mechanical ventilation data were in pressure-based mode, while the remaining 730 or 26.8% of the data were in volume-based modes. The median [interquartile range, IQR] age and BMI of the patient cohort are 63 [55–66] years and 25.2 [23.0–28.2] kg/m<sup>2</sup> respectively. The CDF plots



**Fig. 2.** Shows the changes in breath-average asynchrony magnitude,  $M_{asyn,avg}$  (red) and AI (blue) between  $t = 60$  min time windows. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



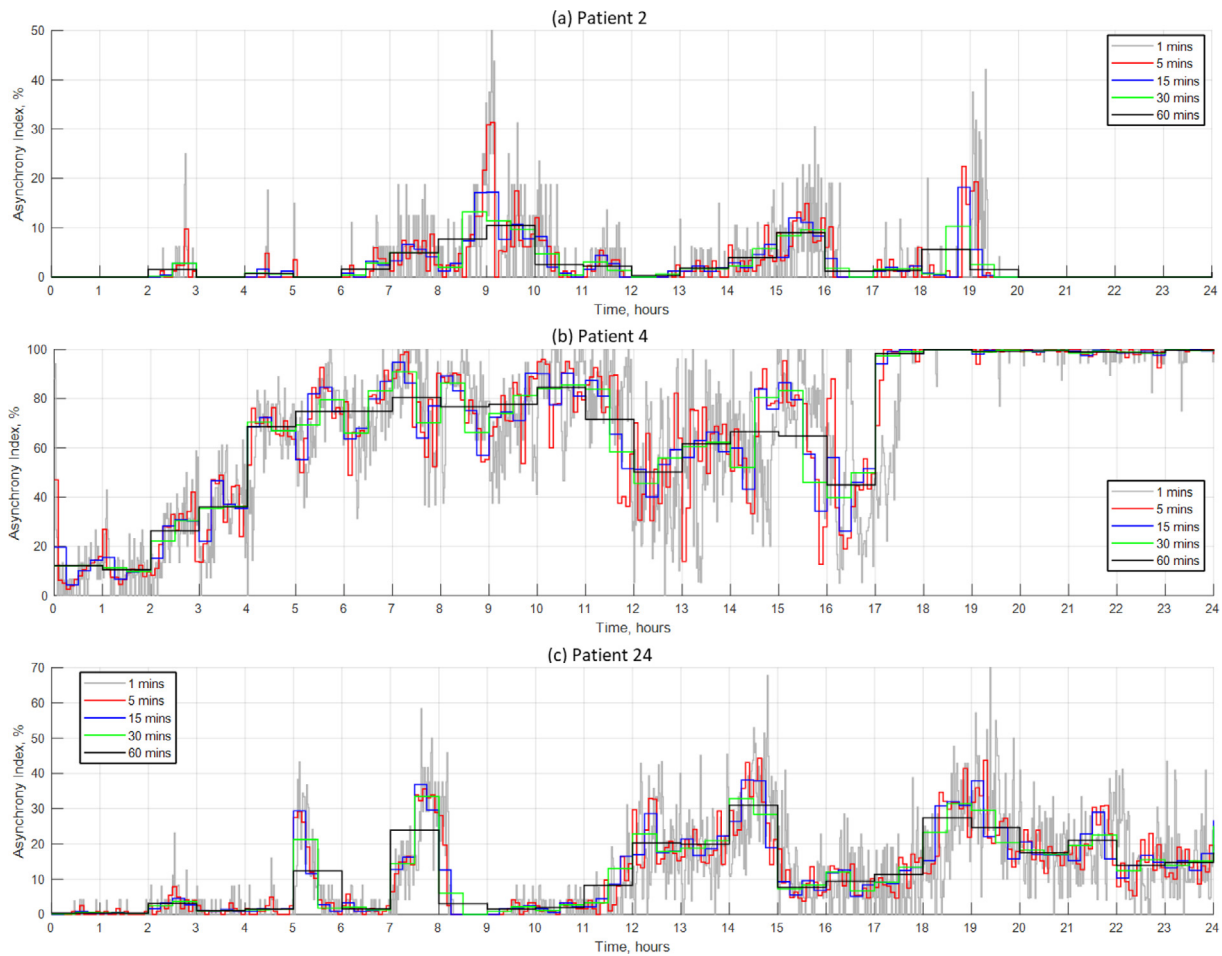
**Fig. 3.** The CDF plots of asynchrony magnitude,  $M_{asyn}$  for all breaths (top row) and asynchrony index using  $t = 30$  s (bottom row) of Patients 2, 4 and 24.

in Fig. 3 show that the distribution of the asynchrony index, AI varies between patients. The distribution of AI presented in Fig. 3 is also reflected in the overall AI values from Table A.1 - Appendix where Patient 2 has a low overall AI at 7.5%, Patient 4 has a high overall AI at 92.6%, while Patient 24 has a moderate overall AI at 22.4%. While the overall AI of the patient cohort has a larger range ( $\sim 5\%$  to  $93\%$ ), the overall  $M_{asyn,avg}$  has a smaller range of  $\sim 27\%$  to  $65\%$  (Table A.2 - Appendix). This difference in range suggests that the AI exhibits more intra- and inter-patient variability within the cohort, whereas for  $M_{asyn,avg}$ , the inter-patient variability is lower. AI strictly quantifies the presence of asynchrony which may vary with patient disease state and the quality of patient-ventilator interactions, leading to larger variations in AI. Concurrently, the magnitude of these asynchronies may remain relatively constant, resulting in smaller variations of  $M_{asyn}$ . Clinically, the evaluation of PVA using both metrics is important to provide a holistic overview of patient disease-states, sedation levels and patient-ventilator interactions.

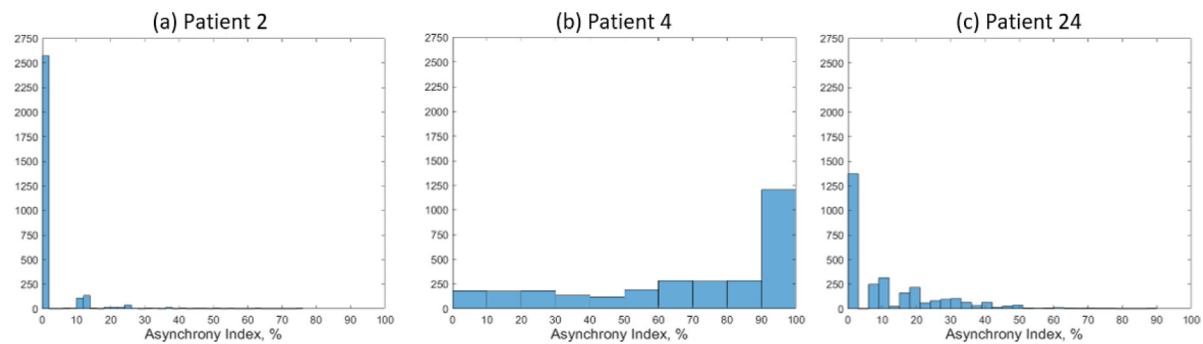
Critical care interventions which include changes to MV settings are usually implemented on an hourly basis (Guo et al., 2016; Pankhurst et al., 2023). A time window of 60 min would capture patient PVA trends within these clinical intervention intervals and has been used for long term PVA analysis (Beitler et al., 2016; Blanch et al., 2015). A Wilcoxon ranksum test was

performed to compare the AI and  $M_{asyn,avg}$  values of different time windows  $t$  with values of  $t = 60$  min to determine if they are representative of data within this longer time window. From Table A.1 - Appendix, AI values determined using  $t \geq 30$  min are statistically similar to  $t = 60$  min. In contrast, most of the patient cohort (29 patients) have significantly different AI values when using  $t \leq 4$  min. All  $M_{asyn,avg}$  values (Table A.2 - Appendix) determined using different  $t$  are statistically similar to  $t = 60$  min, except for Patient 4 ( $t = 30$  s and 1 min), suggesting that a time window of  $t \geq 1$  min would allow observation of granular changes in AI and  $M_{asyn,avg}$ , while ensuring the calculated values are representative of longer temporal trends. Besides that, 26 out of 30 patients (86.7%) had an overall AI greater than 10% signifying that the incidence of asynchrony is common in majority of the patients.

The AI and  $M_{asyn,avg}$  plots for the first 24 h of MV are plotted for 3 patients using different time windows in Fig. 4 and Fig. 6 respectively. These plots illustrate the variations in AI and  $M_{asyn,avg}$  trends with different levels of data granularity, represented by different time windows  $t$ . The plots also show significant intra-patient temporal variations in AI and  $M_{asyn,avg}$ . From Fig. 4b, it is observed that Patient 4 experiences high rates of PVA at a time of 17 h, where AI > 90%. This is likely due to the combination of an increase in patient respiratory drive and



**Fig. 4.** Asynchrony index (AI) plots for the first 24 h of MV data using 1 min (grey), 5 min (red), 15 min (blue), 30 min (green) and 60 min (black) for (a) Patient 2, (b) Patient 4, and (c) Patient 24. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

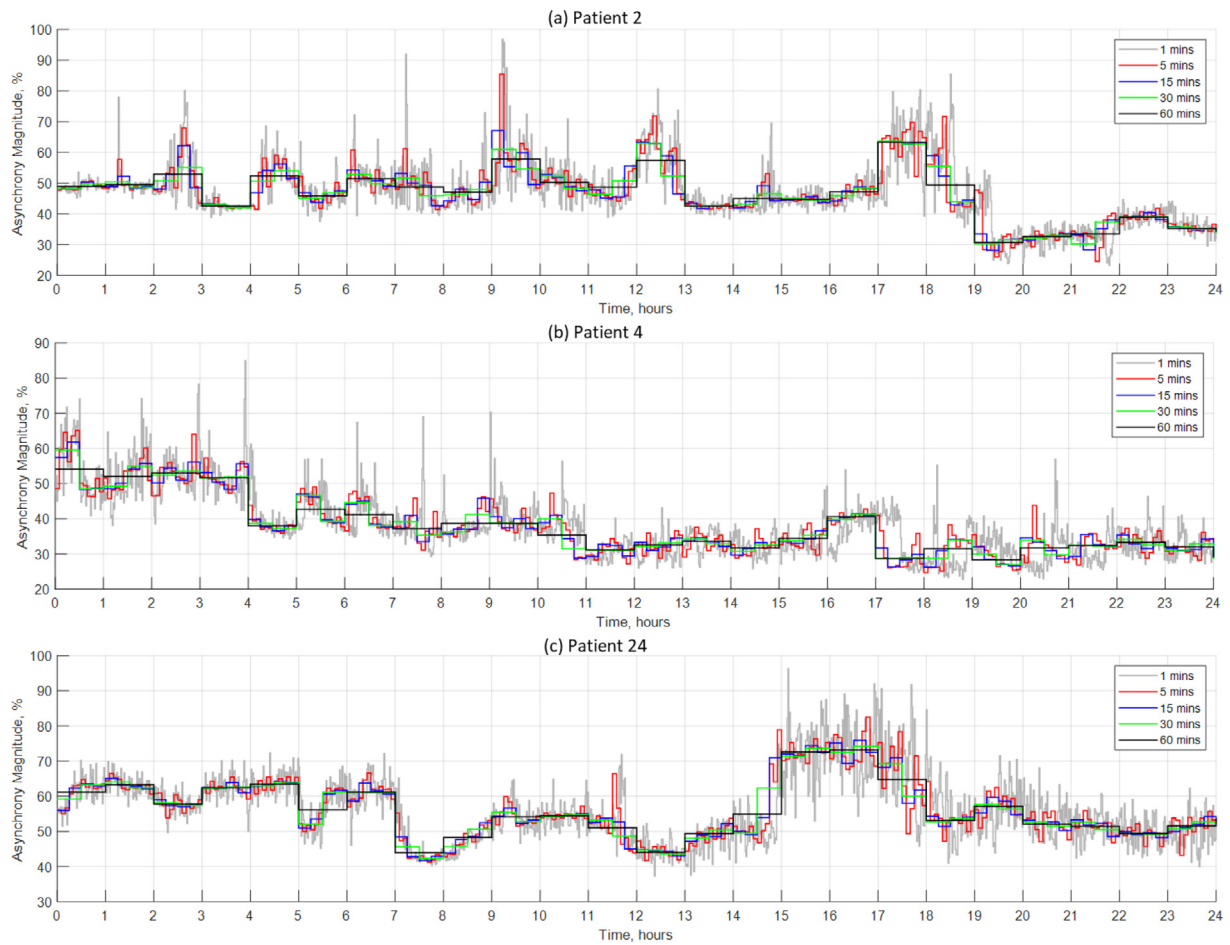


**Fig. 5.** Histograms of AI values using  $t = 30$  s for the first 24 h of MV for (a) Patient 2, (b) Patient 4, and (c) Patient 24. The distributions of AI for these 3 patients are non-normal (Kolmogorov Smirnov test,  $p < 0.05$ ).

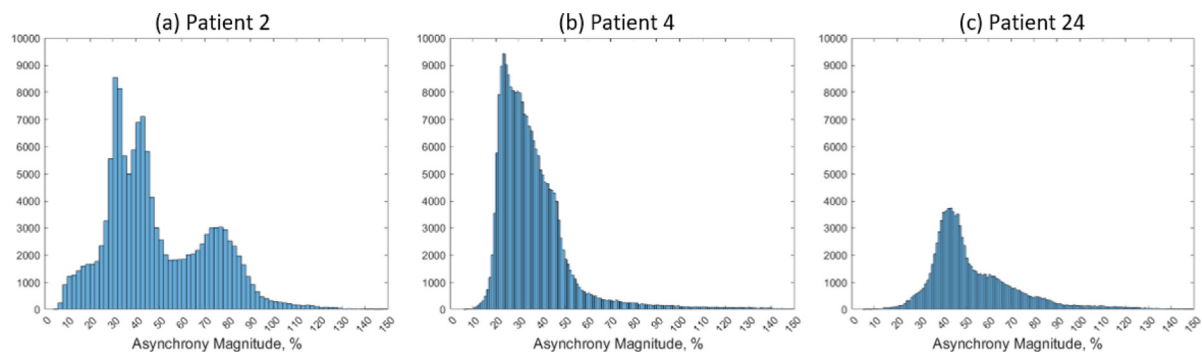
the mismatch between ventilator delivery and patient respiratory demand, resulting in persistent incidences of PVA. Further, the histograms for AI (Fig. 5) and  $M_{asyn,avg}$  (Fig. 7) show that the distribution of AI is highly skewed whereas the distribution of  $M_{asyn,avg}$  exhibits characteristics of a bimodal (Patient 2, Fig. 7a) and a unimodal (Patients 4 and 24, Fig. 7b and c) Gaussian distribution respectively. It is also observed that a high AI may not necessarily translate to a high  $M_{asyn,avg}$  as seen in Patient 4 (Figs. 4b and 6b) between a time of 17–24 h. Furthermore, smaller time windows such as  $t = 5$  min show abrupt changes in patient AI and  $M_{asyn,avg}$  which deviate from values of larger time windows (ie,  $t = 60$  min). This smaller time window allows

for the observation of the granular changes in AI and  $M_{asyn,avg}$  which may be missed by using longer time windows. However, too short of a time window (ie,  $t \leq 1$  min) may lack clinical practicality as it might not be feasible for manual, bedside and continuous real-time implementation of short-term changes of MV settings. Further, the application of very brief time windows for real-time MV treatment may also subject patients to frequent and significant changes in MV settings.

Bedside detection of PVA in a clinical domain traditionally relies on the visual examination of the patients' respiratory pressure and/or flow waveforms (Ramirez & Arellano, 2017; Ramirez et al., 2017). However, this approach requires properly trained



**Fig. 6.** Breath-average magnitude of asynchrony ( $M_{\text{asyn,avg}}$ ) plots for the first 24 h of MV data using 1 min (grey), 5 min (red), 15 min (blue), 30 min (green) and 60 min (black) for (a) Patient 2, (b) Patient 4, and (c) Patient 24. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 7.** Histograms of breath-average magnitude of asynchrony ( $M_{\text{asyn,avg}}$ ) values for the first 24 h of MV for (a) Patient 2, (b) Patient 4, and (c) Patient 24. The distributions of  $M_{\text{asyn,avg}}$  for these 3 patients are non-normal (Kolmogorov Smirnov test,  $p < 0.05$ ).

clinicians to be constantly at the bedside, where the use of automated PVA monitoring systems can help overcome this limitation. The present model-based methods of quantifying PVA necessitate the explicit modelling of each analysed breath while requiring careful constraints of model parameters and discerning data point selection (Ang, Chiew, Vu, & Cove, 2022). Therefore, multiple efforts have attempted to use machine learning (ML) algorithms or models have been proposed for automated PVA detection (Ang, Loo, et al., 2022d; Chatburn & Mireles-Cabodevila, 2020; Damanhuri et al., 2023; Gutierrez, 2020; Loo et al., 2018; Obeso et al., 2023; Pan et al., 2021; Rehm et al., 2020; Zhang et al., 2020), classification (Chong et al., 2021; Hao et al., 2020; Rehm

et al., 2018), quantification of magnitude (Ang, Chiew, Vu, & Cove, 2022; Loo et al., 2021), and prediction (Marchuk et al., 2018).

In this study, a ML approach was implemented as it eliminates the need to mathematically model respiratory waveforms which can exhibit considerable variability both within and among patients particularly in the presence of patient respiratory effort. The use of a ML approach reduces the demand for computational resources, in particular. Thus, it holds promise for clinical applications, particularly in the real-time evaluation of patient-ventilator interaction and eventually automated control of MV care (Chase et al., 2023, 2021).

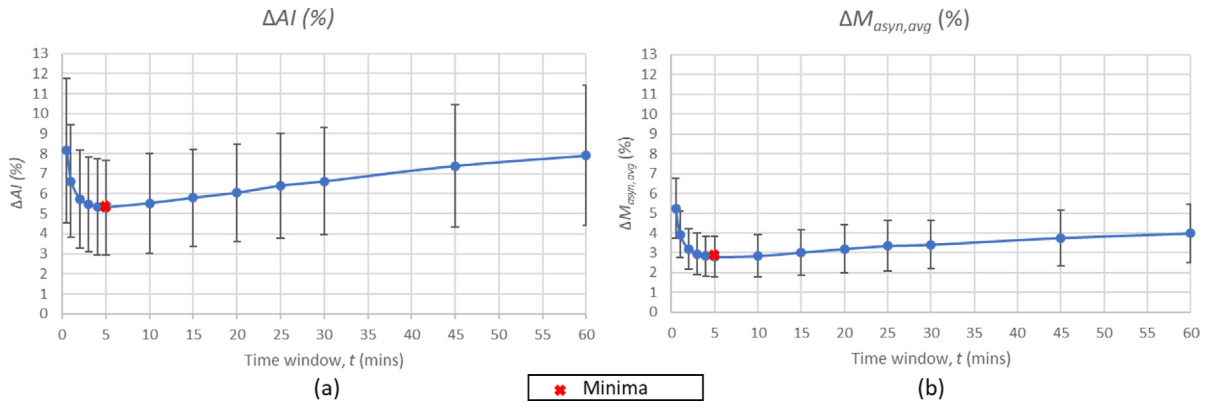


Fig. 8. The mean and standard deviation  $\Delta AI$  (a) and  $\Delta M_{asyn,avg}$  (b) for the patient cohort with varying time windows,  $t$ .

Table 4

The  $\Delta AI$  values of the patient cohort with varying time windows,  $t$ .

Patient	30 s	1 min	2 min	3 min	4 min	5 min	10 min	15 min	20 min	25 min	30 min	45 min	60 min
1	5.87	4.46	3.71	3.58	3.48	3.54	3.98	4.49	4.80	4.94	5.39	6.08	6.09
2	3.90	3.33	3.00	2.91	2.89	2.94	3.00	3.03	3.26	3.31	3.64	4.07	3.98
3	9.78	8.01	6.47	6.02	5.71	5.75	5.92	6.28	6.59	6.84	7.34	8.06	8.63
4	5.45	4.21	3.51	3.36	3.26	3.42	3.58	3.85	3.88	4.29	4.40	4.12	4.02
5	4.82	4.25	3.73	3.62	3.54	3.57	3.97	4.00	4.34	4.42	4.72	5.11	6.06
6	3.99	3.12	2.87	2.78	2.71	2.97	2.76	3.15	3.41	3.22	3.18	4.07	4.45
7	6.58	5.00	4.20	3.74	3.77	3.83	3.96	4.28	4.53	5.02	5.24	5.64	6.38
8	11.37	8.64	6.36	5.45	5.02	4.88	5.18	5.53	6.18	7.02	6.98	8.50	9.25
9	2.98	2.43	2.09	1.85	1.62	1.62	1.99	2.37	2.61	2.65	3.16	4.06	5.28
10	10.92	8.18	7.07	7.16	7.05	7.49	8.40	9.02	8.54	9.89	10.85	10.97	11.83
11	12.14	9.05	7.79	7.52	7.54	7.33	7.22	7.53	8.11	8.22	8.65	9.64	10.13
12	10.60	8.47	7.38	7.45	7.82	8.19	8.68	8.77	8.61	9.10	9.17	10.75	10.52
13	9.45	7.90	7.01	6.88	6.48	7.05	7.89	8.13	9.48	10.57	11.49	14.62	17.52
14	7.83	5.89	4.68	4.20	4.05	3.76	3.70	4.06	4.45	4.70	5.07	6.33	6.00
15	8.24	6.56	6.28	6.74	7.03	7.40	8.30	8.73	9.33	10.18	9.90	10.94	11.52
16	4.75	5.14	4.95	4.62	4.26	3.72	4.01	4.58	4.85	5.04	5.17	6.67	7.05
17	3.45	3.51	3.81	4.33	4.39	4.56	5.43	6.30	6.71	7.35	7.39	8.34	7.31
18	11.36	9.69	4.33	3.82	3.63	8.46	8.77	8.53	8.67	8.71	8.42	9.29	10.10
19	7.80	5.70	8.92	9.04	8.80	3.50	3.31	3.24	3.32	3.56	3.66	4.11	4.40
20	15.93	12.54	10.79	9.23	8.39	7.53	7.22	7.86	7.92	8.26	8.60	8.92	9.30
21	14.30	11.30	9.61	9.49	9.89	9.54	10.60	9.89	9.88	9.92	9.42	9.90	9.39
22	3.90	3.14	2.43	2.42	2.20	2.10	1.93	2.23	2.19	2.30	2.52	2.49	2.55
23	6.49	5.33	4.53	4.20	4.07	4.16	4.34	4.85	5.15	5.47	5.67	6.04	6.20
24	11.45	8.61	6.81	6.08	5.44	5.23	4.65	4.82	5.44	5.28	5.68	6.18	6.12
25	2.84	2.40	2.29	2.31	2.51	2.66	3.07	3.51	3.83	4.22	4.53	5.44	5.37
26	10.29	8.93	7.50	6.55	5.95	5.81	4.86	4.72	4.83	4.74	4.80	4.87	5.93
27	12.30	10.05	8.49	8.11	7.62	7.05	7.06	7.19	7.39	8.47	8.12	7.88	10.14
28	8.09	7.52	6.67	6.03	6.04	5.95	6.57	6.91	7.34	7.52	8.47	9.79	11.45
29	11.97	10.20	10.00	10.58	11.03	11.29	11.17	11.38	11.11	11.87	12.53	14.07	15.72
30	5.82	5.01	4.43	4.34	4.22	4.22	3.94	4.43	4.53	4.91	4.42	4.66	4.35
<b>Mean</b>	<b>8.16</b>	<b>6.62</b>	<b>5.72</b>	<b>5.48</b>	<b>5.35</b>	<b>5.32</b>	<b>5.51</b>	<b>5.79</b>	<b>6.04</b>	<b>6.40</b>	<b>6.62</b>	<b>7.39</b>	<b>7.90</b>
<b>Stdev<sup>a</sup></b>	<b>3.60</b>	<b>2.80</b>	<b>2.43</b>	<b>2.37</b>	<b>2.39</b>	<b>2.37</b>	<b>2.50</b>	<b>2.43</b>	<b>2.41</b>	<b>2.63</b>	<b>2.68</b>	<b>3.06</b>	<b>3.50</b>

<sup>a</sup> Stdev – Standard deviation.

Existing studies lack consensus on a suitable time window to evaluate the incidences of PVA in MV patients, and none have investigated the effects of different time windows on the metrics used to quantify PVA (AI and  $M_{asyn,avg}$ ). The choice of a time window impacts the feasibility and effectiveness of clinical interventions where longer time windows may offer a comprehensive view of PVA trends but may not be suitable for immediate clinical interventions. Conversely, shorter time windows provide real-time insights into patient PVA incidences but may require rapid clinical decision-making. The metrics,  $\Delta AI$  and  $\Delta M_{asyn,avg}$  effectively describe per-interval changes in AI and  $M_{asyn,avg}$  respectively. Thus, an ideal time window should be able to provide sufficient granularity to detect changes in patient asynchrony while minimising  $\Delta AI$  and  $\Delta M_{asyn,avg}$  to reduce excessive fluctuations in patient AI and  $M_{asyn,avg}$  during real-time monitoring. The  $\Delta AI$  and  $\Delta M_{asyn,avg}$  calculated for all patients are presented in Tables 4 and 5 respectively. The cohort mean  $\Delta AI$  and  $\Delta M_{asyn,avg}$

exhibit a converging trend with a minima at  $t = 5$  min and with values of  $5.32 \pm 2.37\%$  and  $2.80 \pm 1.03\%$ , respectively, and is also illustrated in Fig. 8. This minima suggests  $t = 5$  min results in the lowest per-interval changes in AI and  $M_{asyn,avg}$ , providing a balance between data resolution and excessive variations in patient AI and  $M_{asyn,avg}$ , thus further justifying the above results and discussion.  $\Delta AI$  and  $\Delta M_{asyn,avg}$  also demonstrate that AI and  $M_{asyn,avg}$  exhibit temporal changes which may differ from patient to patient, thus highlighting the need for continuous and long-term PVA monitoring.

Clinically, the use of  $t = 5$  min for assessing PVA captures longer term trends of AI and  $M_{asyn,avg}$ . This insight into the broader trends of PVA over time can be valuable for clinicians in identifying patterns and overall prevalence of PVA occurrence within specific patients. This choice is supported by the statistical similarity observed in AI and  $M_{asyn,avg}$  values between  $t = 5$  min and  $t > 5$  min, as shown in Tables A.1 and A.2 of Appendix.



**Table 5**  
The  $\Delta M_{\text{asyn,avg}}$  values of the patient cohort with varying time windows,  $t$ .

Patient	30 s	1 min	2 min	3 min	4 min	5 min	10 min	15 min	20 min	25 min	30 min	45 min	60 min
1	3.69	2.65	2.12	1.99	1.84	1.87	1.89	2.07	2.14	2.31	2.41	2.65	2.96
2	5.48	3.71	2.86	2.48	2.32	2.29	2.17	2.20	2.44	2.52	2.85	3.21	3.28
3	5.04	3.73	3.08	2.86	2.84	2.77	2.83	2.98	3.13	3.21	3.25	3.45	3.57
4	5.16	3.73	3.10	3.03	3.05	3.07	3.66	4.05	4.31	4.41	4.43	4.00	3.81
5	3.05	2.36	2.08	1.97	1.99	2.01	2.28	2.68	3.00	3.25	3.41	3.41	4.12
6	2.38	1.76	1.40	1.31	1.24	1.19	1.39	1.71	2.06	2.29	2.05	2.39	2.35
7	5.37	4.13	3.34	3.17	3.28	3.34	3.98	4.66	4.68	5.15	4.89	6.12	6.36
8	6.18	4.74	3.61	3.23	3.09	2.88	2.88	3.12	3.36	3.40	3.70	3.96	4.56
9	4.83	3.46	2.63	2.23	2.04	2.13	1.99	2.16	2.06	2.19	2.25	2.43	2.77
10	4.13	2.97	2.37	1.90	1.94	1.99	1.85	1.86	2.03	1.87	1.77	1.91	1.31
11	4.85	3.48	2.77	2.54	2.41	2.40	2.55	2.82	2.98	3.20	3.38	3.99	3.78
12	5.91	4.53	3.74	3.42	3.61	3.41	3.50	3.52	3.61	3.74	3.74	4.73	4.92
13	8.20	6.24	5.43	5.09	4.76	4.78	4.55	4.85	4.68	5.24	5.23	5.77	6.30
14	4.61	3.47	2.83	2.58	2.43	2.53	2.81	3.06	3.39	3.39	3.84	4.34	4.72
15	8.23	5.90	4.65	4.48	4.36	4.44	4.78	4.96	5.31	5.59	5.74	5.75	6.21
16	2.46	1.78	1.47	1.44	1.34	1.23	1.31	1.44	1.58	1.64	1.71	2.13	1.98
17	7.26	5.52	4.72	4.31	4.19	4.14	4.06	3.78	3.93	3.99	3.81	4.38	5.05
18	6.83	5.83	2.92	2.64	2.46	5.64	5.72	6.00	6.46	6.25	5.91	6.39	7.14
19	5.30	3.92	5.60	5.81	5.47	2.31	2.36	2.63	2.68	2.88	3.10	3.53	4.01
20	5.60	4.19	3.14	2.67	2.40	2.29	2.08	2.24	2.30	2.36	2.44	2.48	2.71
21	6.55	5.07	4.12	3.99	3.92	3.97	4.12	4.07	4.40	4.45	4.68	5.32	5.03
22	7.26	5.57	4.41	3.98	3.96	3.66	3.59	3.79	4.18	4.61	4.72	4.97	5.04
23	5.40	3.89	2.97	2.70	2.53	2.41	2.25	2.28	2.32	2.38	2.50	2.48	2.82
24	6.03	4.32	3.42	2.93	2.76	2.54	2.24	2.07	2.25	2.34	2.42	2.61	3.06
25	4.68	3.51	3.00	2.99	3.05	3.20	3.50	4.06	4.77	5.22	5.40	6.47	6.13
26	4.64	3.58	2.87	2.51	2.43	2.29	2.19	2.25	2.36	2.54	2.72	2.97	3.54
27	6.22	4.78	3.60	3.53	3.07	3.03	2.93	3.20	3.43	3.74	3.41	3.81	3.63
28	4.95	3.83	2.94	2.60	2.62	2.50	2.42	2.53	2.57	2.69	2.71	2.68	3.31
29	2.81	2.12	1.75	1.69	1.63	1.63	1.60	1.76	1.70	1.92	1.99	2.16	2.59
30	4.51	3.22	2.52	2.24	2.06	2.00	1.91	1.88	1.95	1.93	2.09	2.13	2.32
<b>Mean</b>	<b>5.25</b>	<b>3.93</b>	<b>3.18</b>	<b>2.94</b>	<b>2.84</b>	<b>2.80</b>	<b>2.85</b>	<b>3.02</b>	<b>3.20</b>	<b>3.36</b>	<b>3.42</b>	<b>3.75</b>	<b>3.98</b>
<b>Stdev<sup>a</sup></b>	<b>1.50</b>	<b>1.18</b>	<b>1.04</b>	<b>1.04</b>	<b>1.01</b>	<b>1.03</b>	<b>1.08</b>	<b>1.13</b>	<b>1.21</b>	<b>1.26</b>	<b>1.23</b>	<b>1.40</b>	<b>1.46</b>

<sup>a</sup> Stdev – Standard deviation.

Previous studies have also indicated that a patient's risk level of asynchrony tends remain relatively stable even over longer time intervals, further justifying the representation of longer term PVA trends with a 5-minute time window (Marchuk et al., 2018). At the same time, using a 5-min time window provides sufficient granularity to detect subtle and meaningful changes in patient AI and  $M_{\text{asyn,avg}}$ . This granularity can provide clinicians with real-time insights into patient PVA trends which facilitates timely interventions and adjustments to MV settings, while avoiding excessive granularity where clinical interventions may not effectively target overall patient-specific PVA trends or may be impractical within such short periods.

A study by Vaporidi et al. found that clusters rather than overall rates of asynchrony were associated with worse outcomes, highlighting the importance of the dosage of asynchrony exposure (Vaporidi et al., 2017). Longitudinally assessing patient PVA trends using smaller time windows (i.e.  $t = 5$  min) enables clusters of asynchronies to be more easily detected, where consecutive time windows of high AI and  $M_{\text{asyn}}$  would indicate the presence of these clusters. In contrast, longer time windows (i.e.  $t = 60$  min) may fail to capture these asynchrony clusters due to the averaging of AI and  $M_{\text{asyn}}$  values over longer intervals as seen in Figs. 4 and 6.

In terms of limitations, this study detects and quantifies the magnitude of asynchrony using ML models which rely on the recorded respiratory waveform data. This reliance may result in misestimation of true asynchrony when compared to gold-standard approaches based on oesophageal pressure monitoring or electrical activity of the diaphragm (EAdi) (Scott, 2011). Thus, further validation of the detected asynchronous breaths via visual inspection by trained clinicians may be required to ascertain the performance of the CNN prior to clinical use. Despite this limitation, this study focuses on optimising the time windows used for assessing asynchrony, providing a foundation for further

refinement and application of optimised time windows in clinical settings. It is also important to note that in this study, AI and  $M_{\text{asyn,avg}}$  is not assessed in the context of particular MV outcomes such as length of MV and mortality. Future studies could investigate how AI and  $M_{\text{asyn,avg}}$  determined using different temporal windows affects various MV outcomes.

Further, respiratory data of the patients analysed in this study were not stratified according to their ventilation modes due to the limited amount of MV data of some patients. This choice is made to ensure a consistent amount of data per patient for the calculation of  $\Delta$ AI and  $\Delta M_{\text{asyn,avg}}$ . Therefore, future work with increased data availability could investigate how different MV modes could impact the selection of the optimal time window  $t$  for PVA analysis. Finally, the dual input CNN used in this study is only trained to detect 5 types of asynchrony: reverse triggering, flow starvation, premature cycling, delayed cycling and double triggering, warranting further development of the model with other asynchrony phenotypes.

## 5. Conclusions

This research presents a longitudinal analysis of the temporal trends of patient-ventilator asynchrony in MV patients by calculating its frequency and magnitude over 14 different time windows of varying durations. The median [IQR] overall AI and  $M_{\text{asyn,avg}}$  for the patient cohort is 24.8 [12.9–46.1]% and 37.2 [33.4–45.3]%, respectively. Analysis of the patient cohort also show significant intra-patient variability in AI and  $M_{\text{asyn,avg}}$ , while the inter-patient variation in AI is greater as compared to  $M_{\text{asyn,avg}}$ . The cohort mean  $\Delta$ AI and  $\Delta M_{\text{asyn,avg}}$  exhibit a converging trend with a minima at  $t = 5$  min and with values of  $5.32 \pm 2.37\%$  and  $2.80 \pm 1.03\%$ , respectively. A time window of  $t = 5$  min was preferred for AI and  $M_{\text{asyn,avg}}$  assessment as it can capture the granular changes in asynchrony while also being

**Table A.1**

The asynchrony index, AI (%) for each patient using varying time windows. For each time window, the median [Interquartile range, IQR] values of all available intervals of length  $t$  are presented. AI values of each time window,  $t$  are compared to  $t = 60$  min and tested for statistical differences using a Wilcoxon Rank Sum test ( $p < 0.05$ ).

Patient	30 s	1 min	2 min	3 min	4 min	5 min	10 min	15 min	20 min	25 min	30 min	45 min	60 min	All <sup>a</sup>
1	0	4.5	4.3	4.5	4.7	4.8	4.9	5.2	4.9	5.0	5.5	5.2	5.7	16.6
	[0-18.2]*	[0-17.4]*	[0-17]*	[0-16.9]*	[0-16.8]*	[0-17.3]*	[0.5-17.7]*	[0.6-17.3]	[0.7-17.7]	[0.9-16.5]	[0.9-16.9]	[1.6-17.4]	[1.8-17.4]	
2	0	0	0	0	0	0	0.6	0.8	0.7	0.8	0.8	1.0	1.5	7.5
	[0-0]*	[0-5.6]*	[0-5.7]*	[0-5.9]*	[0-5.7]*	[0-6.2]*	[0-6.7]*	[0-6.8]*	[0-7.1]	[0-7.6]	[0-7.6]	[0.1-9.1]	[0.1-8.9]	
3	42.9	42.1	41.7	41.2	41	41.2	41.1	40.8	40.9	40.9	41.4	41.4	41.4	57.7
	[11.1-100.0]	[12.5-100.0]	[13.3-98.2]*	[14.8-98.7]*	[15-99]*	[15.7-98.8]	[16-98.8]	[18.1-98.6]	[17.2-98.2]	[19.2-98.2]	[19.2-98.4]	[18.7-97.6]	[18-97.6]	
4	100.0	100.0	100	100	98.9	99.0	98.6	98.4	98.2	98.0	97.9	97.6	97.7	92.6
	[90.9-100.0]*	[91.3-100]*	[91.9-100]	[91.4-100]	[91.7-100]	[91.5-100.0]*	[91.6-100]*	[92.0-100]*	[92-99.7]*	[91.9-99.6]*	[92.5-99.6]	[93.0-99.3]	[93.2-98.9]	
5	0	0	0	0	0	0	0.8	1.1	1.2	1.3	1.5	1.7	2.1	13.8
	[0-7.1]*	[0-8.3]*	[0-8]*	[0-8.1]*	[0-8]*	[0-8]*	[0-8.3]*	[0-8.3]*	[0-8.3]*	[0-7.9]	[0-8.7]	[0.2-10.1]	[0.2-9.2]	
6	0	0	0	0	0	0	0	0.4	0.5	0.3	0.7	0.8	0.8	7.3
	[0-0]*	[0-0]*	[0-2.9]*	[0-3.3]*	[0-3]*	[0-3.1]*	[0-3.0]	[0-3.5]	[0-3.1]	[0-3.1]	[0-2.9]	[0-4.1]	[0-2.7]	
7	0	0	0	2.1	1.8	2.0	2.4	2.9	3.1	3.0	3.5	3.5	3.5	12.6
	[0-12.5]*	[0-14.3]*	[0-14.3]*	[0-14.3]*	[0-13.9]*	[0-14.0]*	[0-13.9]	[0-14.6]	[0-15.0]	[0.1-15.7]	[0.2-14.5]	[0.2-15.9]	[0.4-15.2]	
8	10	10.0	11.1	11.6	11.8	11.8	12.2	13.3	13.5	13.1	12.4	13.3	14.2	24.0
	[0-33.3]*	[0-33.3]*	[0-33.3]*	[0-32.9]*	[1.1-32.7]*	[1.1-32.8]	[1.3-32.4]	[1.5-32.5]	[1.8-32]	[1.9-32.6]	[2.4-32.6]	[3.3-31.9]	[4.1-32.6]	
9	0	0	0	0	0	0	0.4	0.3	0.3	0.2	0.2	0.3	0.3	10.4
	[0-0]*	[0-3.8]*	[0-3.2]*	[0-3.1]*	[0-3.3]*	[0-3.1]*	[0-4.2]	[0-4.3]	[0-5.0]	[0-4.6]	[0-4.8]	[0-5.2]	[0.1-5.2]	
10	42.9	43.6	42.9	45.2	44.4	44.9	45.6	46.2	49.8	51.3	47.6	51.1	41.5	49.0
	[0-88.9]	[0-88.2]	[0-89.3]*	[0-89.5]*	[1.8-89.3]*	[1.6-89.4]	[4.1-89.3]	[4.2-89.0]	[4.3-87.9]	[5.7-87.1]	[5.0-87.8]	[7.4-86.2]	[8.3-83.9]	
11	31.3	34.6	36	36.8	37.7	37.6	39.3	40.4	39.8	41.4	41.0	43.2	41.2	47.1
	[0-70.6]	[0-68.8]	[3.2-67.3]*	[3.6-67.1]*	[4.1-65.6]*	[4.5-64.8]	[4.8-65.7]	[5.1-63.8]	[5.3-62.8]	[5.2-63.2]	[5.1-61.7]	[5.8-60.7]	[6.6-60.2]	
12	42.9	43.6	42.2	42.9	44.2	44.9	45.7	45.0	45.0	47.0	45.0	46.8	49.9	50.8
	[0-90.9]	[6.3-92.9]	[6.6-91.1]*	[8.1-91.1]*	[8.2-91.3]*	[9-91.1]	[9.6-90.6]	[9.9-89.6]	[11.1-90.1]	[10.0-88.3]	[8.4-86.4]	[7.9-87.8]	[6.9-86.2]	
13	44.4	42.9	41.9	41.9	43	41	40.7	43.3	44.2	45.8	46.6	50.3	40.8	47.1
	[0-100]	[6.7-100]	[7.7-100]*	[9.5-97.6]*	[9.7-97.9]*	[9.7-98.2]	[10.3-98.1]	[12.7-97.8]	[12.6-98.1]	[14.2-98.2]	[14.1-97.6]	[13.7-96.5]	[15.9-95.7]	
14	10.0	14.3	14.3	13.7	13.5	13.3	13.7	14.1	12.4	12.9	13.6	14.5	16.3	28.2
	[0-50.0]*	[0-48.3]	[0-47.8]*	[0-47.6]*	[0-46.7]*	[0-46.8]	[0.5-45.5]	[0.3-45.3]	[0.3-45.4]	[0.3-48.7]	[0.3-47.1]	[0.6-48.8]	[0.5-49.0]	
15	0	5.3	5.3	5.6	5.7	6.1	7.7	8.0	9.0	8.2	8.9	9.7	9.1	25.6
	[0-30.0]*	[0-29.4]*	[0-29.7]*	[0-28.9]*	[0-29.3]*	[0-27.8]*	[1.2-28.2]	[1.9-26.5]	[2.2-29.5]	[2.4-29.2]	[2.8-27.5]	[3.6-27.6]	[4.7-32.3]	
16	60.0	56.3	53.5	57.4	55.7	57.0	53.5	48.8	50.1	47.2	47.1	53.0	43.6	59.7
	[0-100.0]	[0-100]	[0-100]*	[1.6-100]*	[2.1-100]*	[3.1-100.0]	[3.8-100.0]	[4.3-100.0]	[4.8-100.0]	[4.9-100.0]	[5.5-100]	[6.3-100.0]	[6.3-100.0]	
17	0	0	0	0	0	0	0	0.6	0.8	1.0	1.1	1.5	2.7	12.6
	[0-0]*	[0-0]*	[0-0]*	[0-2.7]*	[0-2.1]*	[0-3.3]*	[0-4.3]*	[0-5.2]*	[0-7.8]*	[0-7.5]*	[0.2-7]	[0.4-8.1]	[0.8-8.4]	
18	12.5	15.4	16.8	17.6	17.4	17.6	17.8	17.8	18.6	18.5	19.0	20.1	19.9	23.3
	[0-36.4]*	[0-34.8]	[0-34.5]*	[0-34.2]*	[0-34.1]*	[0-34.0]	[0-33.7]	[0-33.9]	[0-33.1]	[0-32.7]	[0-33.2]	[0.1-33.7]	[0.1-32.9]	
19	0	6.3	5.9	6.9	7.5	7.9	9.2	10.1	10.2	10.6	10.5	10.7	10.0	21.8
	[0-33.3]*	[0-33.3]*	[0-33.3]*	[0-33.3]*	[0-34.7]*	[1.3-33.3]	[1.6-34.9]	[1.9-34.6]	[2.6-34.1]	[2.9-36.0]	[3.2-37.0]	[3.5-38.1]	[3.7-38.3]	
20	12.5	17.6	21.1	21.6	21.9	21.5	22.5	21.8	22.4	22.7	23.9	24.8	26.3	35.2
	[0-54.5]*	[0-52.6]*	[0-51.3]*	[2-50]*	[2.8-48.8]*	[3.8-49.0]	[5.3-48.3]	[5.6-48.3]	[6.5-48.4]	[6.2-47.3]	[6.6-47.5]	[7.1-48.0]	[7.4-48.1]	
21	27.3	27.3	26.7	27.1	28.0	25.9	25.7	24.9	28.3	30.1	25.2	26.6	26.6	43.1
	[0-76.9]	[7.1-77.8]	[9.5-77.8]*	[10.1-78.8]*	[10.7-78.3]*	[10.9-78.6]	[12.8-76.6]	[12.9-75.8]	[12.9-76.4]	[13.7-76.0]	[14.4-76.7]	[18.0-76.4]	[16.9-78.1]	
22	0	0	0	0	0	0	0	0.4	0.3	0.3	0.4	0.4	0.4	5.4
	[0-0]*	[0-5.3]*	[0-5.3]*	[0-5.5]*	[0-5.7]*	[0-5.9]*	[0-6.5]*	[0-6.5]	[0-6.5]	[0-7.1]	[0-7.0]	[0-6.6]	[0-7.7]	
23	10.0	5.4	5.6	6.7	6.6	6.6	7.5	7.9	7.5	7.8	7.8	8.1	10.4	39.0
	[0-80.0]*	[0-80.0]*	[0-80.4]*	[1.2-80.7]*	[1.3-80.4]*	[1-80.5]	[1-80.8]	[1.3-80.0]	[1.5-79.5]	[1.4-80.9]	[1.5-79.7]	[1.5-78.4]	[1.6-78.8]	
24	18.2	17.6	17.4	17.7	17.9	17.5	18.1	17.3	18.2	18.2	18.7	18.5	20.1	22.4
	[0-33.3]	[5.6-33.3]	[8.3-32.6]*	[9.1-32.3]*	[9.2-31.8]*	[9.5-32.2]	[10.1-32.7]	[10.4-32.4]	[10.1-31.9]	[10.1-32.3]	[11.1-32.1]	[10.3-31.9]	[11.4-30.6]	
25	0	0	0	0	0	0	0	0.3	0.2	0.5	0.5	0.9	0.8	11.5
	[0-0]*	[0-0]*	[0-2.3]*	[0-2.7]*	[0-2.6]*	[0-2.9]*	[0-4.6]*	[0-4.7]*	[0-5.1]*	[0-5.3]	[0-5.5]	[0.1-6.4]	[0.1-6.4]	
26	11.8	13.3	14.9	15.6	16.3	16.4	16.9	17.6	18.4	17.9	18.5	18.2	18.3	20.1
	[0-30.0]*	[2.9-29.3]*	[3.3-29.1]*	[3.7-28.4]*	[4.2-28.4]*	[4.4-28.1]	[5.2-27.9]	[5.5-27.8]	[6.0-26.8]	[6.6-27.2]	[6.6-27.5]	[6.9-27.2]	[6.9-26.3]	
27	42.9	43.5	42.2	41.8	42.3	41.7	40.6	41.3	40.1	39.8	40.1	42.2	42.3	43.3
	[18.2-63.6]	[21.7-60.9]	[24-61.7]*	[24.7-62.4]*	[25.1-62.2]*	[25.9-62.2]	[25.2-62.2]	[26.4-62.8]	[28.6-62.8]	[27.5-63.3]	[29.0-63.5]	[30.1-63.1]	[29.3-63.2]	
28	12.5	13.0	13.2	12.4	12.9	13.6	15.3	14.1	14.1	14.1	14.1	14.1	18.1	37.5
	[0-64.3]*	[0-64.1]	[1.9-64.1]*	[2.2-64.7]*	[2.3-64.1]*	[2.6-64.6]	[2.9-64.3]	[3-67]	[3.1-64.8]	[3.4-63.9]	[3.4-63.2]	[3.3-65.7]	[3.8-61.4]	
29	64.3	63.6	63.8	64	64	64.3	64.2	64.3	62.6	63.3	63.4	65.4	65.8	63.8
	[28.6-93.3]	[30.4-92.0]	[32.1-90.6]*	[33.3-89.9]*	[33.7-89.3]*	[33.9-88.6]	[36.2-87.6]	[37.9-86.2]	[37.5-85.9]	[35.4-86.2]	[37.1-83.2]	[40.1-84.2]	[38.6-82.2]	
30	0	0	2.3	2.5	2.9	3.1	3.8	3.9	4.5	4.5	4.9	5.5	5.9	9.6
	[0-10]*	[0-11.1]*	[0-10.9]*	[0-10.8]*	[0-10.8]*	[0-10.9]*	[0-11.6]	[0.3-11]	[0.4-10.8]	[0.6-11.0]	[0.7-11.5]	[0.6-11.9]	[0.9-10.9]	
<b>Median</b>	10.9	13.2	13.8	13.1	13.3	13.1	13.7	14.7	13.8	15.5	15.9	14.9	17.2	24.8
<b>IQR</b>	[0-40.0]	[0-40.2]	[0.6-40.2]	[2.2-40.1]	[2.1-40.2]	[2.3-40.2]	[2.8-40.3]	[3.1-40.7]	[3.4-40.0]	[3.3-40.6]	[3.9-40.8]	[3.9-42]	[4.1-41.1]	[12.9-46.1]

\* Values between the two time windows,  $t$  in comparison are significantly different ( $p < 0.05$ ).

<sup>a</sup> All refers to a single interval with a time window equal to the total duration of MV for a particular patient.

representative of longer temporal trends, thus preventing excessive variations in patient AI and  $M_{asym,avg}$ . Overall, continuous, real-time and long-term monitoring of asynchrony could provide better insight towards patient-ventilator interaction, potentially leading to improved MV treatment and patient outcomes.

**CRedit authorship contribution statement**

**Christopher Yew Shuen Ang:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Yeong Shiong Chiew:** Conceptualization, Supervision, Writing – review & editing. **Xin Wang:** Supervision, Writing – review & editing. **Ean Hin Ooi:** Supervision, Writing – review & editing. **Mohd Basri Mat Nor:** Data curation, Supervision, Writing – review & editing. **Matthew E. Cove:** Supervision, Writing – review & editing. **J. Geoffrey Chase:** Supervision, Writing – review & editing.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Data availability**

Data will be made available on request.

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**Appendix**

Tables A.1 and A.2.

**Table A.2**

The breath-average asynchrony magnitude,  $M_{\text{asyn,avg}}$  (%) for each patient using varying time windows. For each time window, the median [Interquartile range, IQR] values of all available intervals of length  $t$  are presented.  $M_{\text{asyn,avg}}$  values of each time window,  $t$  are compared to  $t = 60$  min and tested for statistical differences using a Wilcoxon Rank Sum test ( $p < 0.05$ ).

Patient	30 s	1 min	2 min	3 min	4 min	5 min	10 min	15 min	20 min	25 min	30 min	45 min	60 min	All*
1	32.3	32.4	32.3	32.3	32.3	32.2	32.3	32.3	32.2	32.3	32.4	32.3	32.3	31.8
2	[28.5-37.1]	[28.9-37.0]	[29.3-37.3]	[29.4-37.3]	[29.4-37.5]	[29.5-37.5]	[29.9-37.5]	[29.9-37.6]	[29.9-37.4]	[30.0-37.4]	[30.2-37.1]	[30.5-37.0]	[30.3-36.7]	[22.8-40.1]
3	30.5	[41.6-56.0]	[41.7-55.8]	[41.8-55.6]	[41.8-55.5]	[41.8-55.4]	[41.7-55.4]	[41.7-55.2]	[41.7-55.2]	[41.6-55.0]	[42.0-54.9]	[41.6-54.8]	[41.7-54.9]	[32.4-66.8]
4	34.3	[21.7-46.2]	[21.5-46.5]	[21.3-46.5]	[21.2-46.7]	[21.0-46.8]	[21.1-46.3]	[20.8-46.1]	[21.1-46.6]	[21.1-46.3]	[21.1-46.6]	[20.9-47.5]	[20.8-46.9]	[21.1-39.7]
5	33.7	[30.1-40.4]	[30.5-40.1]	[30.7-40.1]	[30.8-40]	[30.8-40.1]	[31.1-39.9]	[31.4-39.8]	[31.2-39.8]	[31.5-39.5]	[31.7-39.3]	[32.0-39.5]	[32.3-39.2]	[25.6-41.9]
6	34.2	34.2	34.3	34.5	34.5	34.5	34.5	34.4	34.4	34.5	34.4	34.6	34.4	[28.4-41.7]
7	34.1	[31.1-36.8]	[31.2-36.9]	[31.3-36.7]	[31.4-36.6]	[31.5-36.7]	[31.4-36.6]	[31.2-36.5]	[32.0-36.5]	[31.9-36.5]	[31.2-36.5]	[31.9-36.6]	[32.7-36.5]	[28.6-38.0]
8	49.6	[38.0-65.2]	[38.3-65.2]	[38.5-65.3]	[38.7-65.6]	[38.7-65.6]	[38.5-65.3]	[38.6-65.3]	[38.6-65.4]	[38.6-65.3]	[38.8-65.9]	[38.8-65.3]	[39.0-64.9]	[32.4-64.2]
9	40.4	[35.2-46.7]	[35.7-46.4]	[36-46.5]	[36.1-46.5]	[36.1-46.5]	[36.1-46.4]	[35.9-46.5]	[36.2-46.6]	[36.0-46.1]	[36.2-46.6]	[36.4-46.9]	[36.0-46.6]	[31.0-46.2]
10	35.4	[32.7-38.5]	[33.2-38.1]	[33.6-37.9]	[33.9-37.6]	[33.8-37.7]	[34.1-37.4]	[34.4-37.6]	[34.6-37.6]	[34.3-37.5]	[34.7-37.8]	[34.3-37.6]	[34.8-37.8]	[29.5-41.3]
11	44.8	[33.9-59.2]	[33.8-60.0]	[33.8-60.4]	[33.7-60.8]	[33.9-60.7]	[33.8-61.2]	[33.9-61.1]	[33.7-61.6]	[33.8-61.0]	[34.0-61.0]	[33.5-61.3]	[33.7-59.8]	[34.0-61.0]
12	33.9	[29.2-39.0]	[29.7-38.7]	[30.1-38.3]	[30.1-38.2]	[30.2-38.2]	[30.3-38.1]	[30.3-37.8]	[30.4-38.0]	[30.3-37.5]	[30.7-37.6]	[30.5-38.1]	[30.7-37.8]	[31.1-37.9]
13	38.0	[31.7-48.8]	[32.5-48.6]	[33.1-48.1]	[33.1-48.1]	[33.2-48.3]	[33.3-48.0]	[33.9-48.2]	[34.0-48.2]	[34.6-47.4]	[34.3-47.1]	[34.9-47]	[35.9-46.3]	[27.1-47.9]
14	59.3	[41.3-66.1]	[41.2-65.8]	[41-65.6]	[41-65.7]	[41-65.4]	[41.0-65.5]	[40.9-65.3]	[40.9-65.1]	[40.9-65.4]	[40.9-65.3]	[40.8-65.2]	[41.0-64.9]	[39.9-73.6]
15	53.3	[29.0-67.2]	[39.6-66.6]	[40-66.4]	[40.5-66.5]	[40.6-66.2]	[40.3-65.7]	[40.8-66.2]	[41.9-65.3]	[42.1-65.6]	[42.3-65.2]	[42.5-65.1]	[43.3-63.2]	[32.1-66.7]
16	25.9	[24.3-30.9]	[24.4-30.7]	[24.4-30.9]	[24.4-30.8]	[24.5-30.7]	[24.5-30.4]	[24.5-30.6]	[24.5-30.7]	[24.4-30.9]	[24.4-30.7]	[24.3-30.6]	[24.6-30.8]	[22.1-28.9]
17	66.9	[60.2-73.3]	[61.6-72.6]	[62.3-71.7]	[62.6-71.6]	[62.8-71.5]	[63.2-71.4]	[63.1-71.1]	[63.5-71.1]	[63.5-71.1]	[63.7-70.0]	[63.4-70.9]	[64.2-70.0]	[51.4-78.1]
18	41.6	[35.1-51.6]	[35.5-51.4]	[35.8-51.2]	[35.8-51.3]	[35.9-51.2]	[35.9-51.0]	[35.8-51.1]	[36.0-50.9]	[36.1-50.9]	[36.3-50.3]	[36.3-50.8]	[36.3-50.4]	[36.9-49.8]
19	61.7	[37.2-74.6]	[36.9-74.5]	[37.1-74.4]	[36.9-74.4]	[37.1-74.4]	[36.8-74.8]	[36.7-74.3]	[36.8-74.4]	[37.0-74.4]	[37.0-74.1]	[37.1-74.1]	[37.0-74.1]	[37.3-74.0]
20	42.9	[37.6-54.8]	[37.9-54.3]	[38.1-54.2]	[38.1-54.1]	[38.1-54.1]	[38.1-54]	[38.1-53.7]	[38.1-54.1]	[38.2-54.6]	[38.2-54.2]	[38.1-54.3]	[38.2-53.7]	[38.2-54.1]
21	36.0	[30.4-41.7]	[30.8-41.6]	[31.2-41.4]	[31.3-41.1]	[31.3-41.2]	[31.2-41.1]	[31.6-41]	[31.8-41.1]	[31.9-41.2]	[32.2-41]	[32.3-40.8]	[32.2-40.9]	[32.4-41.1]
22	54.3	[40.4-69.2]	[40.7-69.8]	[41-70.7]	[41.1-70.3]	[41.2-70.7]	[41.6-70.5]	[41.2-70.8]	[41.6-70.0]	[42.4-70.3]	[41.7-70.4]	[42.2-70.2]	[41.6-69.3]	[42.1-68.7]
23	48.0	[40.0-62.3]	[40.3-62.5]	[40.5-62.9]	[40.6-63.2]	[40.6-63]	[40.7-63.3]	[40.7-64.0]	[41.0-63.9]	[41.0-64.1]	[40.8-64.0]	[40.9-63.9]	[41.2-64.2]	[41.0-64.2]
24	52.1	[46.9-58.1]	[47.7-57.4]	[48.2-56.9]	[48.4-56.6]	[48.4-56.6]	[48.5-56.4]	[48.8-56.3]	[48.8-56.1]	[48.8-56.4]	[49.0-55.8]	[49.0-56.2]	[49.0-56.4]	[40.7-61.5]
25	36.6	[23.6-56.2]	[23.6-56.5]	[23.6-56.5]	[23.3-57]	[23.4-56.9]	[23.2-57.2]	[23.2-57.2]	[23.3-56.5]	[22.9-57.5]	[22.8-56.8]	[22.7-57.2]	[22.8-57.5]	[22.6-57.0]
26	50.7	[45.2-59.8]	[45.5-59.4]	[45.7-58.9]	[45.8-58.8]	[45.8-58.9]	[45.9-58.7]	[45.9-58.4]	[46.1-58.4]	[46.1-58.4]	[46.1-57.9]	[46.2-58.4]	[46.2-58]	[46.4-57.5]
27	47.2	[42.0-58.3]	[42.9-58.2]	[43.5-58]	[43.6-58.3]	[43.9-57.9]	[44.0-58.0]	[44.1-58.2]	[44.1-58.7]	[44.0-58.4]	[43.9-57.8]	[44.1-58.1]	[44.3-58.7]	[44.4-58.9]
28	42.6	[34.5-55.6]	[34.4-55.6]	[34.3-55.7]	[34.3-55.7]	[34.3-55.6]	[34.2-55.7]	[34.3-55.8]	[34.2-56.0]	[34.3-55.9]	[34.3-56.1]	[34.3-56.1]	[34.3-56.4]	[34.4-56.7]
29	32.1	[29.0-35.8]	[29.2-35.7]	[29.4-35.4]	[29.4-35.4]	[29.5-35.2]	[29.5-35.2]	[29.6-35.1]	[29.9-35.1]	[29.9-35.1]	[29.8-35.2]	[29.7-34.7]	[29.3-35.7]	[25.2-36.2]
30	38.2	[33.6-59.2]	[33.7-59.7]	[33.8-59.8]	[33.8-60]	[33.8-59.7]	[33.9-59.7]	[34.1-59.9]	[34.1-60.2]	[33.9-60.0]	[34.1-59.9]	[34.1-59.9]	[34.1-59.2]	[34.3-59.5]
Median	41.0	41.2	41.3	41.4	41.5	41.5	41.5	41.5	41.7	41.6	41.7	41.8	41.6	37.2
IQR	[34.2-49.5]	[34.3-50.3]	[34.4-50.5]	[34.5-50.4]	[34.5-50.6]	[34.6-50.5]	[34.8-50.8]	[35.0-50.7]	[35.1-50.9]	[35.3-50.8]	[35.1-51.0]	[35.1-50.8]	[35.1-51.1]	[33.4-45.3]

\* Values between the two time windows,  $t$  in comparison are significantly different ( $p < 0.05$ ).

† All refers to a single interval with a time window equal to the total duration of MV for a particular patient.

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