Montelukast reduces COVID-19 risk: real-time meta analysis of 9 studies

@CovidAnalysis, July 2025, Version 9 https://c19early.org/mkmeta.html

Abstract

Significantly lower risk is seen for hospitalization and cases. 4 studies from 4 independent teams in 4 countries show significant benefit.

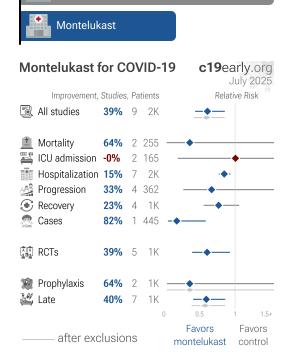
Meta analysis using the most serious outcome reported shows 39% [14-56%] lower risk. Results are similar for Randomized Controlled Trials and higher quality studies.

Currently there is limited data, with only 37 control events for the most serious outcome in trials to date.

2 RCTs with 664 patients have not reported results (up to 3 years late) 1,2 .

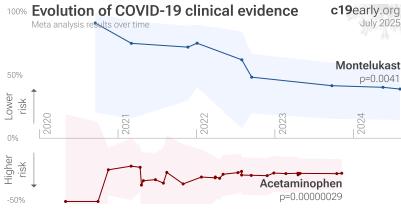
Montelukast has a boxed warning for neuropsychiatric side effects ³.

No treatment is 100% effective. Protocols combine safe and effective options with individual risk/benefit analysis and monitoring. Other treatments are more effective. Montelukast currently has no early treatment studies. All data and sources to reproduce this analysis are in the appendix.



Serious Outcome Risk

Control



MONTELUKAST FOR COVID-19 - HIGHLIGHTS

Montelukast reduces risk with very high confidence for hospitalization and in pooled analysis, and low confidence for recovery and cases.

32nd treatment shown effective in November 2021, now with p = 0.0041 from 9 studies.

Real-time updates and corrections with a consistent protocol for 172 treatments. Outcome specific analysis and combined evidence from all studies including treatment delay, a primary confounding factor.



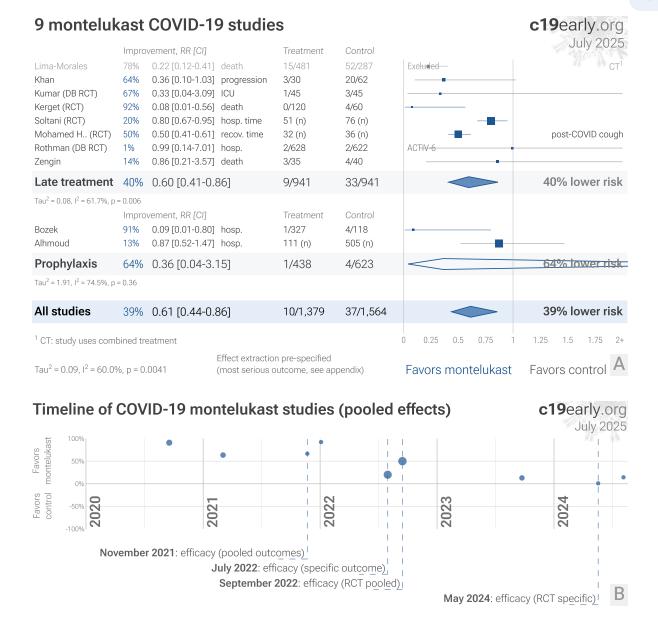


Figure 1. A. Random effects meta-analysis. This plot shows pooled effects, see the specific outcome analyses for individual outcomes. Analysis validating pooled outcomes for COVID-19 can be found below. Effect extraction is pre-specified, using the most serious outcome reported. For details see the appendix. B. Timeline of results in montelukast studies. The marked dates indicate the time when efficacy was known with a statistically significant improvement of ≥10% from ≥3 studies for pooled outcomes, one or more specific outcome, pooled outcomes in RCTs, and one or more specific outcome in RCTs. Efficacy based on RCTs only was delayed by 9.8 months, compared to using all studies. Efficacy based on specific outcomes was delayed by 8.2 months, compared to using pooled outcomes in RCTs.

Introduction

Immediate treatment recommended

SARS-CoV-2 infection primarily begins in the upper respiratory tract and may progress to the lower respiratory tract, other tissues, and the nervous and cardiovascular systems, which may lead to cytokine storm, pneumonia, ARDS, neurological injury⁵⁻¹⁷ and cognitive deficits^{8,13}, cardiovascular complications¹⁸⁻²², organ failure, and death. Even mild untreated infections may result in persistent cognitive deficits²³—the spike protein binds to fibrin leading to fibrinolysis-resistant blood clots, thromboinflammation, and neuropathology. Minimizing replication as early as possible is recommended.



Montelukast reduces COVID-19 risk: real-time meta analysis of 9 studies

Many treatments are expected to modulate infection

SARS-CoV-2 infection and replication involves the complex interplay of 100+ host and viral proteins and other factors^{A,24-31}, providing many therapeutic targets for which many existing compounds have known activity. Scientists have predicted that over 9,000 compounds may reduce COVID-19 risk³², either by directly minimizing infection or replication, by supporting immune system function, or by minimizing secondary complications.

Extensive supporting research

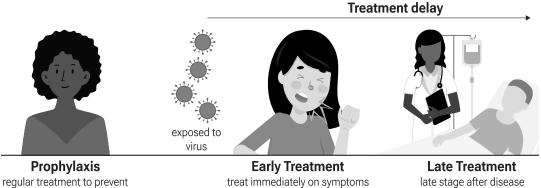
In Silico studies predict inhibition of SARS-CoV-2 with montelukast or metabolites via binding to the spike ^{B,33} (and specifically the receptor binding domain ^{C,34}), M^{pro D,33}, RNA-dependent RNA polymerase ^{E,33,35}, PLpro ^{F,33}, nucleocapsid ^{G,33}, and helicase ^{H,33} proteins. Montelukast inhibits SARS-CoV-2 omicron infection in Vero cells at 1µM³⁴ and inhibits platelet activation induced by plasma from COVID-19 patients³⁶.

Analysis

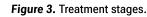
We analyze all significant controlled studies of montelukast for COVID-19. Search methods, inclusion criteria, effect extraction criteria (more serious outcomes have priority), all individual study data, PRISMA answers, and statistical methods are detailed in Appendix 1. We present random effects meta-analysis results for all studies, studies within each treatment stage, individual outcomes, Randomized Controlled Trials (RCTs), and higher quality studies.

Treatment timing

Figure 3 shows stages of possible treatment for COVID-19. Prophylaxis refers to regularly taking medication before becoming sick, in order to prevent or minimize infection. Early Treatment refers to treatment immediately or soon after symptoms appear, while Late Treatment refers to more delayed treatment.



progression



or shortly thereafter

Preclinical Research

or minimize infections

In Silico studies predict inhibition of SARS-CoV-2 with montelukast or metabolites via binding to the spike ^{B,33} (and specifically the receptor binding domain ^{C,34}), M^{pro D,33}, RNA-dependent RNA polymerase ^{E,33,35}, PLpro ^{F,33}, nucleocapsid ^{G,33}, and helicase ^{H,33} proteins. Montelukast inhibits SARS-CoV-2 omicron infection in Vero cells at 1μ M³⁴ and inhibits platelet activation induced by plasma from COVID-19 patients³⁶.

3 In Silico studies support the efficacy of montelukast³³⁻³⁵.

2 In Vitro studies support the efficacy of montelukast^{34,36}.



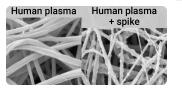


Figure 2. SARS-CoV-2 spike protein fibrin binding leads to thromboinflammation and neuropathology, from⁴.

Preclinical research is an important part of the development of treatments, however results may be very different in clinical trials. Preclinical results are not used in this paper.

Results

Table 1 summarizes the results for all stages combined, for Randomized Controlled Trials, after exclusions, and for specific outcomes. Table 2 shows results by treatment stage. Figure 4 plots individual results by treatment stage. Figure 5, 6, 7, 8, 9, 10, and 11 show forest plots for random effects meta-analysis of all studies with pooled effects, mortality results, ICU admission, hospitalization, progression, recovery, and cases.

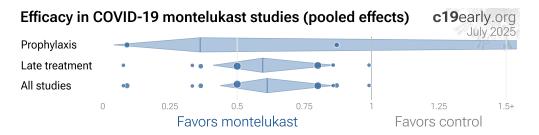
	Relative Risk	Studies	Patients
All studies	0.61 [0.44-0.86] **	9	2,943
After exclusions	0.60 [0.42-0.85] **	8	2,868
RCTs	0.61 [0.40-0.93] *	5	1,715
Mortality	0.36 [0.04-3.49]	2	255
ICU admission	1.00 [0.19-5.21]	2	165
Hospitalization	0.85 [0.77-0.93] ***	7	2,725
Recovery	0.77 [0.56-1.06]	4	1,535
RCT hospitalization	0.82 [0.73-0.93] **	3	1,497

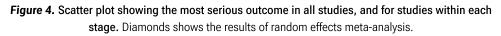
Table 1. Random effects meta-analysis for all stages combined,
for Randomized Controlled Trials, after exclusions, and for
specific outcomes. Results show the relative risk with treatment
and the 95% confidence interval. * p<0.05</th>** p<0.01.</th>

	Late treatment	Prophylaxis
All studies	0.60 [0.41-0.86] **	0.36 [0.04-3.15]
After exclusions	0.58 [0.39-0.86] **	0.36 [0.04-3.15]
RCTs	0.61 [0.40-0.93]*	
Mortality	0.36 [0.04-3.49]	
ICU admission	1.00 [0.19-5.21]	
Hospitalization	0.85 [0.77-0.94] **	0.36 [0.04-3.15]
Recovery	0.77 [0.56-1.06]	
RCT hospitalization	0.82 [0.73-0.93] **	

Table 2. Random effects meta-analysis results by treatmentstage. Results show the relative risk with treatment and the 95%confidence interval. * p<0.05</td>** p<0.01.</td>







9 monteluk	kast	COVID-19	studie	S				c19early.org
	Impro	vement, RR [CI]		Treatment	Control			July 2025
Lima-Morales	78%	0.22 [0.12-0.41] d	death	15/481	52/287	Excluded	_	CT ¹
Khan	64%	0.36 [0.10-1.03] p	progression	3/30	20/62			
Kumar (DB RCT)	67%	0.33 [0.04-3.09] 10	CU	1/45	3/45			
Kerget (RCT)	92%	0.08 [0.01-0.56] d	death	0/120	4/60			
Soltani (RCT)	20%	0.80 [0.67-0.95] h	nosp. time	51 (n)	76 (n)			
Mohamed H (RCT)	50%	0.50 [0.41-0.61] r	recov. time	32 (n)	36 (n)			post-COVID cough
Rothman (DB RCT)	1%	0.99 [0.14-7.01] h	nosp.	2/628	2/622	ACTIV-6		
Zengin	14%	0.86 [0.21-3.57] d	death	3/35	4/40			
Late treatment	40%	0.60 [0.41-0.86	6]	9/941	33/941			40% lower risk
Tau ² = 0.08, I ² = 61.7%, p	= 0.006							
	Impro	vement, RR [CI]		Treatment	Control			
Bozek	91%	0.09 [0.01-0.80] h	nosp.	1/327	4/118			
Alhmoud	13%	0.87 [0.52-1.47] h	nosp.	111 (n)	505 (n)			
Prophylaxis	64%	0.36 [0.04-3.15	5]	1/438	4/623	<		64% lower risk
Tau ² = 1.91, I ² = 74.5%, p	= 0.36							
All studies	39%	0.61 [0.44-0.86	6]	10/1,379	37/1,564			39% lower risk
¹ CT: study uses coml	bined tr	eatment				 0 0.25	0.5 0.75 1	1.25 1.5 1.75 2+
Tau ² = 0.09, I ² = 60.09	‰, p = 0.			n pre-specified utcome, see ap	pendix)	Favors	montelukast	Favors control

Figure 5. Random effects meta-analysis for all studies. This plot shows pooled effects, see the specific outcome analyses for individual outcomes. Analysis validating pooled outcomes for COVID-19 can be found below. Effect extraction is prespecified, using the most serious outcome reported. For details see the appendix.

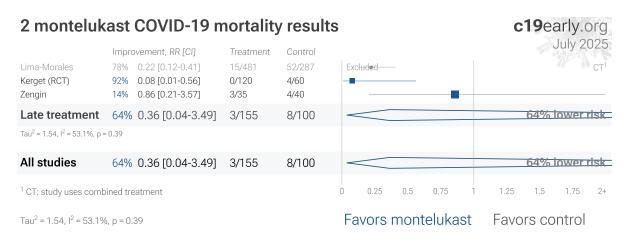
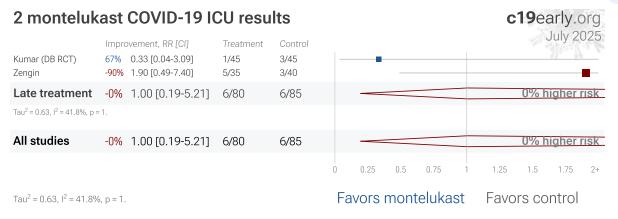
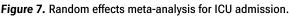


Figure 6. Random effects meta-analysis for mortality results.







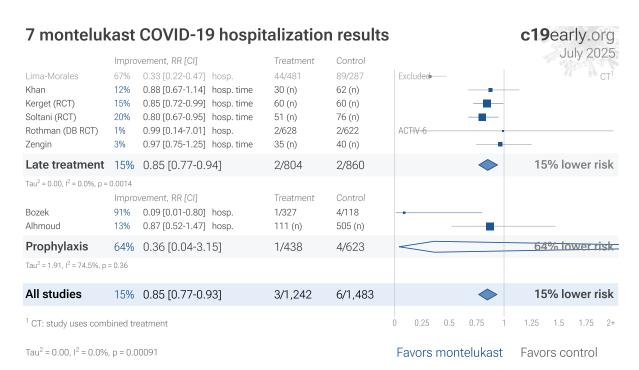
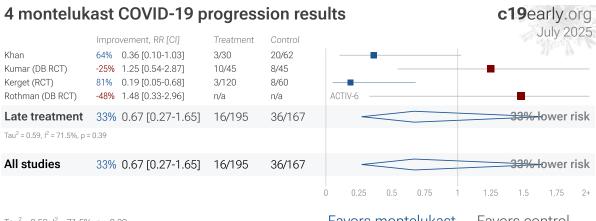


Figure 8. Random effects meta-analysis for hospitalization.



Tau² = 0.59, I² = 71.5%, p = 0.39

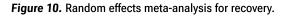
Favors montelukast

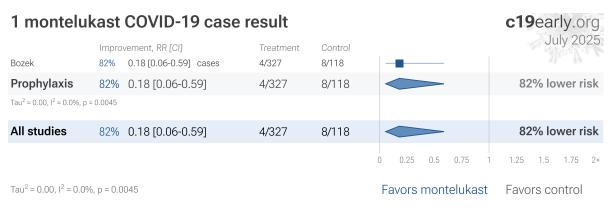
Favors control

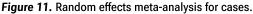
Figure 9. Random effects meta-analysis for progression.



4 monteluk	4 montelukast COVID-19 recovery results c19 early.org							
	Impro	ovement, RR [CI]	Treatment	Control		July 2025		
Lima-Morales Kumar (DB RCT) Soltani (RCT) Mohamed H (RCT) Rothman (DB RCT)	59% 0% 25% 50% 2%	0.41 [0.30-0.55] no recov. 1.00 [0.64-1.56] no disch. 0.75 [0.64-0.88] no recov. 0.50 [0.41-0.61] recov. time 0.98 [0.89-1.10] no recov.	75/481 21/45 51 (n) 32 (n) 628 (n)	118/287 21/45 76 (n) 36 (n) 622 (n)	ACTIV-6	post-COVID cough		
. ,		0.77 [0.56-1.06]	21/756	21/779		- 23% lower risk		
Tau ² = 0.09, I ² = 91.6%, p	= 0.11							
All studies	23%	0.77 [0.56-1.06]	21/756	21/779		- 23% lower risk		
¹ CT: study uses com	bined tr	eatment			0 0.25 0.5 0.75 1	1.25 1.5 1.75 2+		
Tau ² = 0.09, I ² = 91.69	%, p = 0	.11			Favors montelukast	Favors control		







Randomized Controlled Trials (RCTs)

Figure 12 shows a comparison of results for RCTs and observational studies. Figure 13, 14, and 15 show forest plots for random effects meta-analysis of all Randomized Controlled Trials, RCT mortality results, and RCT hospitalization results. RCT results are included in Table 1 and Table 2.

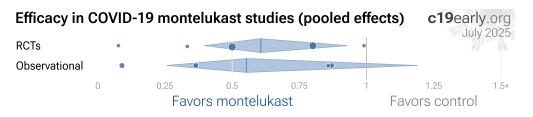


Figure 12. Results for RCTs and observational studies.

RCTs have many potential biases

RCTs help to make study groups more similar and can provide a higher level of evidence, however they are subject to many biases ³⁷, and analysis of double-blind RCTs has identified extreme levels of bias ³⁸. For COVID-19, the overhead may delay treatment, dramatically compromising efficacy; they may encourage monotherapy for simplicity at the cost of efficacy which may rely on combined or synergistic effects; the participants that sign up may not reflect real world usage or the population that benefits most in terms of age, comorbidities, severity of illness, or other factors;



standard of care may be compromised and unable to evolve quickly based on emerging research for new diseases; errors may be made in randomization and medication delivery; and investigators may have hidden agendas or vested interests influencing design, operation, analysis, reporting, and the potential for fraud. All of these biases have been observed with COVID-19 RCTs. There is no guarantee that a specific RCT provides a higher level of evidence.

Conflicts of interest for COVID-19 RCTs

RCTs are expensive and many RCTs are funded by pharmaceutical companies or interests closely aligned with pharmaceutical companies. For COVID-19, this creates an incentive to show efficacy for patented commercial products, and an incentive to show a lack of efficacy for inexpensive treatments. The bias is expected to be significant, for example Als-Nielsen et al. analyzed 370 RCTs from Cochrane reviews, showing that trials funded by for-profit organizations were 5 times more likely to recommend the experimental drug compared with those funded by nonprofit organizations. For COVID-19, some major philanthropic organizations are largely funded by investments with extreme conflicts of interest for and against specific COVID-19 interventions.

RCTs for novel acute diseases requiring rapid treatment

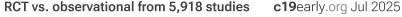
High quality RCTs for novel acute diseases are more challenging, with increased ethical issues due to the urgency of treatment, increased risk due to enrollment delays, and more difficult design with a rapidly evolving evidence base. For COVID-19, the most common site of initial infection is the upper respiratory tract. Immediate treatment is likely to be most successful and may prevent or slow progression to other parts of the body. For a non-prophylaxis RCT, it makes sense to provide treatment in advance and instruct patients to use it immediately on symptoms, just as some governments have done by providing medication kits in advance. Unfortunately, no RCTs have been done in this way. Every treatment RCT to date involves delayed treatment. Among the 172 treatments we have analyzed, 67% of RCTs involve very late treatment 5+ days after onset. No non-prophylaxis COVID-19 RCTs match the potential real-world use of early treatments. They may more accurately represent results for treatments that require visiting a medical facility, e.g., those requiring intravenous administration.

RCT bias for widely available treatments

RCTs have a bias against finding an effect for interventions that are widely available — patients that believe they need the intervention are more likely to decline participation and take the intervention. RCTs for montelukast are more likely to enroll low-risk participants that do not need treatment to recover, making the results less applicable to clinical practice. This bias is likely to be greater for widely known treatments, and may be greater when the risk of a serious outcome is overstated. This bias does not apply to the typical pharmaceutical trial of a new drug that is otherwise unavailable.

Observational studies have been shown to be reliable

Evidence shows that observational studies can also provide reliable results. *Concato et al.* found that well-designed observational studies do not systematically overestimate the magnitude of the effects of treatment compared to RCTs. *Anglemyer et al.* analyzed reviews comparing RCTs to observational studies and found little evidence for significant differences in effect estimates. We performed a similar analysis across



Low-cost treatments High-profit treatments	1.00					_	*				
All treatments	0.98	[0.92-1.05]					\diamondsuit	2%	diff	eren	се
			0 h	RCT	īs sł	างพ		1.25 RCT	Ts sl	now	-

Figure 16. For COVID-19, observational study results do not systematically differ from RCTs, RR 0.98 [0.92-1.05] across 172 treatments ⁴⁰.

the 172 treatments we cover, showing no significant difference in the results of RCTs compared to observational studies, RR 0.98 [0.92-1.05]⁴³. Similar results are found for all low-cost treatments, RR 1.00 [0.91-1.09]. High-cost treatments show a non-significant trend towards RCTs showing greater efficacy, RR 0.92 [0.84-1.02]. Details can be found in the supplementary data. *Lee et al.* showed that only 14% of the guidelines of the Infectious Diseases Society of America were based on RCTs. Evaluation of studies relies on an understanding of the study and potential biases.



Limitations in an RCT can outweigh the benefits, for example excessive dosages, excessive treatment delays, or remote survey bias may have a greater effect on results. Ethical issues may also prevent running RCTs for known effective treatments. For more on issues with RCTs see ^{45,46}.

Using all studies identifies efficacy 8+ months faster (9+ months for low-cost treatments)

Currently, 55 of the treatments we analyze show statistically significant efficacy or harm, defined as $\geq 10\%$ decreased risk or >0% increased risk from ≥ 3 studies. Of these, 58% have been confirmed in RCTs, with a mean delay of 7.7 months (64% with 8.9 months delay for low-cost treatments). The remaining treatments either have no RCTs, or the point estimate is consistent.

Summary

We need to evaluate each trial on its own merits. RCTs for a given medication and disease may be more reliable, however they may also be less reliable. For off-patent medications, very high conflict of interest trials may be more likely to be RCTs, and more likely to be large trials that dominate meta analyses.

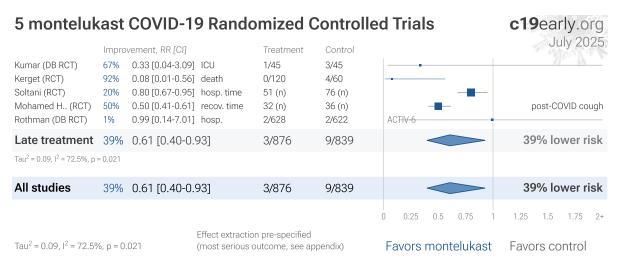
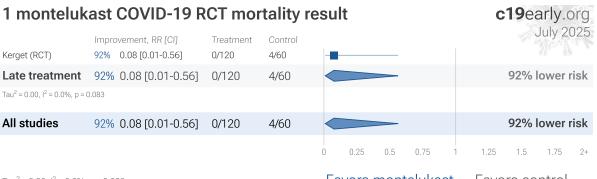


Figure 13. Random effects meta-analysis for all Randomized Controlled Trials. This plot shows pooled effects, see the specific outcome analyses for individual outcomes. Analysis validating pooled outcomes for COVID-19 can be found below. Effect extraction is pre-specified, using the most serious outcome reported. For details see the appendix.



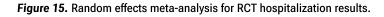
Tau² = 0.00, I² = 0.0%, p = 0.083

Favors montelukast Favors control

Figure 14. Random effects meta-analysis for RCT mortality results.



3 monteluk	c19early.org					
	Impro	ovement, RR [Cl]	Treatment	Control		July 2025
Kerget (RCT) Soltani (RCT) Rothman (DB RCT)	15% 20% 1%	0.85 [0.72-0.99] hosp. time 0.80 [0.67-0.95] hosp. time 0.99 [0.14-7.01] hosp.	60 (n) 51 (n) 2/628	60 (n) 76 (n) 2/622	ACT IV-6	Nr. V.
Late treatment	18%	0.82 [0.73-0.93]	2/739	2/758	\diamond	18% lower risk
Tau ² = 0.00, I ² = 0.0%, p =	0.0013					
All studies	18%	0.82 [0.73-0.93]	2/739	2/758		18% lower risk
					0 0.25 0.5 0.75 1	1.25 1.5 1.75 2+
Tau ² = 0.00, I ² = 0.0%	, p = 0.0	0013			Favors montelukast	Favors control



Unreported RCTs

2 montelukast RCTs have not reported results ^{1,2}. The trials report report an estimated total of 664 patients. The results are delayed from 1.5 years to over 3 years.

Exclusions

To avoid bias in the selection of studies, we analyze all non-retracted studies. Here we show the results after excluding studies with major issues likely to alter results, non-standard studies, and studies where very minimal detail is currently available. Our bias evaluation is based on analysis of each study and identifying when there is a significant chance that limitations will substantially change the outcome of the study. We believe this can be more valuable than checklist-based approaches such as Cochrane GRADE, which can be easily influenced by potential bias, may ignore or underemphasize serious issues not captured in the checklists, and may overemphasize issues unlikely to alter outcomes in specific cases (for example certain specifics of randomization with a very large effect size and well-matched baseline characteristics).

The studies excluded are as below. Figure 17 shows a forest plot for random effects meta-analysis of all studies after exclusions.

Zengin, unadjusted results with minimal group details.



Montelukast reduces COVID-19 risk: real-time meta analysis of 9 studies

8 monteluk	kast CO	OVID-19 studie	es after e	xclusior	าร	c19early.org
Khan Kumar (DB RCT) Kerget (RCT)	64% 0.3 67% 0.3	ent, RR [CI] 36 [0.10-1.03] progression 33 [0.04-3.09] ICU 38 [0.01-0.56] death	Treatment 3/30 1/45 0/120	Control 20/62 3/45 4/60		July 2025
Soltani (RCT) Mohamed H (RCT) Rothman (DB RCT)	50% 0.5	80 [0.67-0.95] hosp. time 50 [0.41-0.61] recov. time 99 [0.14-7.01] hosp.	51 (n) 32 (n) 2/628	76 (n) 36 (n) 2/622		post-COVID cough
Late treatment	42% 0.5	58 [0.39-0.86]	6/906	29/901		42% lower risk
Tau ² = 0.09, I ² = 67.8%, p	= 0.0069					
Bozek Alhmoud	91% 0.0	ent, RR [CI] 09 [0.01-0.80] hosp. 37 [0.52-1.47] hosp.	Treatment 1/327 111 (n)	Control 4/118 505 (n)		
Prophylaxis	64% 0.3	36 [0.04-3.15]	1/438	4/623		64% lower risk
Tau ² = 1.91, I ² = 74.5%, p	= 0.36					
All studies	40% 0.6	60 [0.42-0.85]	7/1,344	33/1,524		40% lower risk
					0 0.25 0.5 0.75	1 1.25 1.5 1.75 2+
Tau ² = 0.09, I ² = 64.89	%, p = 0.004		n pre-specified outcome, see ap	pendix)	Favors montelukas	t Favors control

Figure 17. Random effects meta-analysis for all studies after exclusions. This plot shows pooled effects, see the specific outcome analyses for individual outcomes. Analysis validating pooled outcomes for COVID-19 can be found below. Effect extraction is pre-specified, using the most serious outcome reported. For details see the appendix.

Heterogeneity

Heterogeneity in COVID-19 studies arises from many factors including:

Treatment delay

The time between infection or the onset of symptoms and treatment may critically affect how well a treatment works. For example an antiviral may be very effective when used early but may not be effective in late stage disease, and may even be harmful. Oseltamivir, for example, is generally only considered effective for influenza when used within 0-36 or 0-48 hours^{48,49}. Baloxavir marboxil studies for influenza also show that treatment delay is critical — *Ikematsu et al.* report an 86% reduction in cases for post-exposure prophylaxis, *Hayden et al.* show a 33 hour reduction in the time to alleviation of symptoms for treatment within 24 hours and a reduction of 13 hours for treatment within 24-48 hours, and *Kumar et al.* report only 2.5 hours improvement for inpatient treatment.

Treatment delay	Result
Post-exposure prophylaxis	86% fewer cases 50
<24 hours	-33 hours symptoms ⁵¹
24-48 hours	-13 hours symptoms ⁵¹
Inpatients	-2.5 hours to improvement 52

Table 3. Studies of baloxavir marboxil for influenza show that early treatment is more effective.



Figure 18 shows a mixed-effects meta-regression for efficacy as a function of treatment delay in COVID-19 studies from 172 treatments, showing that efficacy declines rapidly with treatment delay. Early treatment is critical for COVID-19.

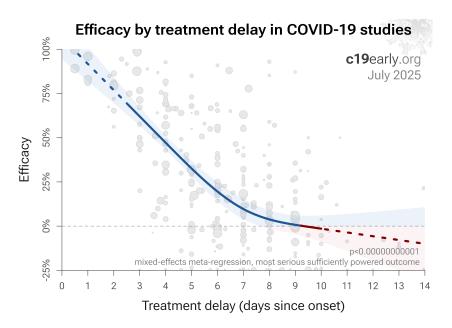


Figure 18. Early treatment is more effective. Meta-regression showing efficacy as a function of treatment delay in COVID-19 studies from 172 treatments.

Patient demographics

Details of the patient population including age and comorbidities may critically affect how well a treatment works. For example, many COVID-19 studies with relatively young low-comorbidity patients show all patients recovering quickly with or without treatment. In such cases, there is little room for an effective treatment to improve results, for example as in López-Medina et al.

SARS-CoV-2 variants

Efficacy may depend critically on the distribution of SARS-CoV-2 variants encountered by patients. Risk varies significantly across variants ⁵⁴, for example the Gamma variant shows significantly different characteristics ⁵⁵⁻⁵⁸. Different mechanisms of action may be more or less effective depending on variants, for example the degree to which TMPRSS2 contributes to viral entry can differ across variants ^{59,60}.

Treatment regimen

Effectiveness may depend strongly on the dosage and treatment regimen.

Medication quality

The quality of medications may vary significantly between manufacturers and production batches, which may significantly affect efficacy and safety. *Williams et al.* analyze ivermectin from 11 different sources, showing highly variable antiparasitic efficacy across different manufacturers. *Xu et al.* analyze a treatment from two different manufacturers, showing 9 different impurities, with significantly different concentrations for each manufacturer.

Other treatments

The use of other treatments may significantly affect outcomes, including supplements, other medications, or other interventions such as prone positioning. Treatments may be synergistic ⁶³⁻⁷⁹, therefore efficacy may depend strongly on combined treatments.



Effect measured

Across all studies there is a strong association between different outcomes, for example improved recovery is strongly associated with lower mortality. However, efficacy may differ depending on the effect measured, for example a treatment may be more effective against secondary complications and have minimal effect on viral clearance.

Meta analysis

The distribution of studies will alter the outcome of a meta analysis. Consider a simplified example where everything is equal except for the treatment delay, and effectiveness decreases to zero or below with increasing delay. If there are many studies using very late treatment, the outcome may be negative, even though early treatment is very effective. All meta analyses combine heterogeneous studies, varying in population, variants, and potentially all factors above, and therefore may obscure efficacy by including studies where treatment is less effective. Generally, we expect the estimated effect size from meta analysis to be less than that for the optimal case. Looking at all studies is valuable for providing an overview of all research, important to avoid cherry-picking, and informative when a positive result is found despite combining less-optimal situations. However, the resulting estimate does not apply to specific cases such as early treatment in high-risk populations. While we present results for all studies, we also present treatment time and individual outcome analyses, which may be more informative for specific use cases.

Pooled Effects

Pooled effects are no longer required to show efficacy as of July 2022

This section validates the use of pooled effects for COVID-19, which enables earlier detection of efficacy, however pooled effects are no longer required for montelukast as of July 2022. Efficacy is now known based on specific outcomes for all studies and when restricted to RCTs. Efficacy based on specific outcomes was delayed by 8.2 months compared to using pooled outcomes. Efficacy based on specific outcomes in RCTs was delayed by 20.1 months compared to using pooled outcomes in RCTs.

Combining studies is required

For COVID-19, delay in clinical results translates into additional death and morbidity, as well as additional economic and societal damage. Combining the results of studies reporting different outcomes is required. There may be no mortality in a trial with low-risk patients, however a reduction in severity or improved viral clearance may translate into lower mortality in a high-risk population. Different studies may report lower severity, improved recovery, and lower mortality, and the significance may be very high when combining the results. *"The studies reported different outcomes"* is not a good reason for disregarding results. Pooling the results of studies reporting different outcomes allows us to use more of the available information. Logically we should, and do, use additional information when evaluating treatments—for example dose-response and treatment delay-response relationships provide additional evidence of efficacy that is considered when reviewing the evidence for a treatment.

Specific outcome and pooled analyses

We present both specific outcome and pooled analyses. In order to combine the results of studies reporting different outcomes we use the most serious outcome reported in each study, based on the thesis that improvement in the most serious outcome provides comparable measures of efficacy for a treatment. A critical advantage of this approach is simplicity and transparency. There are many other ways to combine evidence for different outcomes, along with additional evidence such as dose-response relationships, however these increase complexity.

Ethical and practical issues limit high-risk trials

Trials with high-risk patients may be restricted due to ethics for treatments that are known or expected to be effective, and they increase difficulty for recruiting. Using less severe outcomes as a proxy for more serious outcomes allows faster and safer collection of evidence.



Validating pooled outcome analysis for COVID-19

For many COVID-19 treatments, a reduction in mortality logically follows from a reduction in hospitalization, which follows from a reduction in symptomatic cases, which follows from a reduction in PCR positivity. We can directly test this for COVID-19.

Analysis of the the association between different outcomes across studies from all 172 treatments we cover confirms the validity of pooled outcome analysis for COVID-19. Figure 19 shows that lower hospitalization is very strongly associated with lower mortality (p < 0.00000000001). Similarly, Figure 20 shows that improved recovery is very strongly associated with lower mortality (p < 0.00000000001). Considering the extremes, *Singh et al.* show an association between viral clearance and hospitalization or death, with p = 0.003 after excluding one large outlier from a mutagenic treatment, and based on 44 RCTs including 52,384 patients. Figure 21 shows that improved viral clearance is strongly associated with fewer serious outcomes. The association is very similar to *Singh et al.*, with higher confidence due to the larger number of studies. As with *Singh et al.*, the confidence increases when excluding the outlier treatment, from p = 0.000000082 to p = 0.000000033.

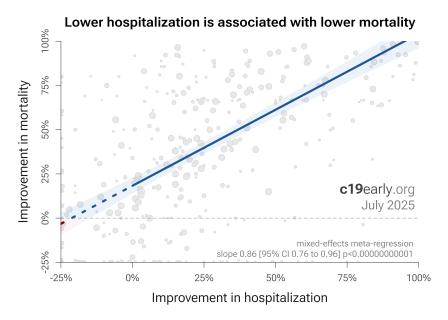


Figure 19. Lower hospitalization is associated with lower mortality, supporting pooled outcome analysis.



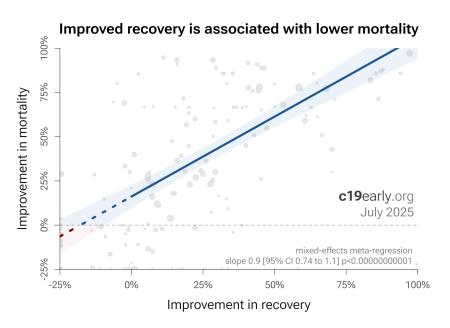
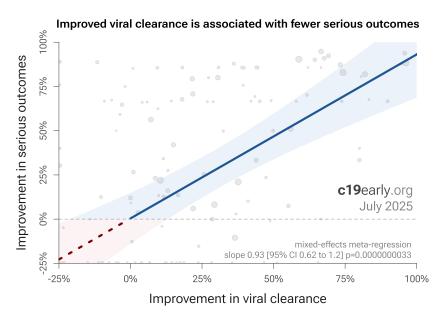
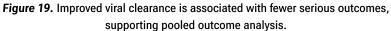


Figure 20. Improved recovery is associated with lower mortality, supporting pooled outcome analysis.

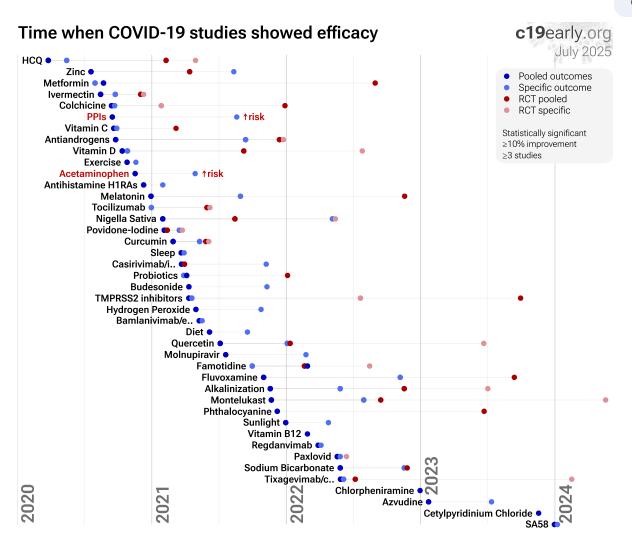


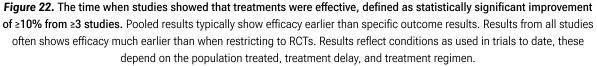


Pooled outcomes identify efficacy 5 months faster (7 months for RCTs)

Currently, 55 of the treatments we analyze show statistically significant efficacy or harm, defined as \geq 10% decreased risk or >0% increased risk from \geq 3 studies. 88% of these have been confirmed with one or more specific outcomes, with a mean delay of 4.9 months. When restricting to RCTs only, 57% of treatments showing statistically significant efficacy/harm with pooled effects have been confirmed with one or more specific outcomes, with a mean delay of 7.3 months. Figure 22 shows when treatments were found effective during the pandemic. Pooled outcomes often resulted in earlier detection of efficacy.







Limitations

Pooled analysis could hide efficacy, for example a treatment that is beneficial for late stage patients but has no effect on viral clearance may show no efficacy if most studies only examine viral clearance. In practice, it is rare for a nonantiviral treatment to report viral clearance and to not report clinical outcomes; and in practice other sources of heterogeneity such as difference in treatment delay is more likely to hide efficacy.

Summary

Analysis validates the use of pooled effects and shows significantly faster detection of efficacy on average. However, as with all meta analyses, it is important to review the different studies included. We also present individual outcome analyses, which may be more informative for specific use cases.

Discussion

Boxed warning

Montelukast has a boxed warning for neuropsychiatric side effects³.



Publication bias

Publishing is often biased towards positive results, however evidence suggests that there may be a negative bias for inexpensive treatments for COVID-19. Both negative and positive results are very important for COVID-19, media in many countries prioritizes negative results for inexpensive treatments (inverting the typical incentive for scientists that value media recognition), and there are many reports of difficulty publishing positive results⁸¹⁻⁸⁴. For montelukast, there is currently not enough data to evaluate publication bias with high confidence.

One method to evaluate bias is to compare prospective vs. retrospective studies. Prospective studies are more likely to be published regardless of the result, while retrospective studies are more likely to exhibit bias. For example, researchers may perform preliminary analysis with minimal effort and the results may influence their decision to continue. Retrospective studies also provide more opportunities for the specifics of data extraction and adjustments to influence results.

Figure 23 shows a scatter plot of results for prospective and retrospective studies. The median effect size for retrospective studies is 39% improvement, compared to 50% for prospective studies, suggesting a potential bias towards publishing results showing lower efficacy.

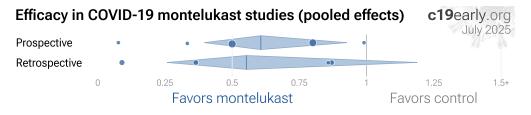


Figure 23. Prospective vs. retrospective studies. The diamonds show the results of random effects meta-analysis.

Funnel plot analysis

Funnel plots have traditionally been used for analyzing publication bias. This is invalid for COVID-19 acute treatment trials — the underlying assumptions are invalid, which we can demonstrate with a simple example. Consider a set of hypothetical perfect trials with no bias. Figure 24 plot A shows a funnel plot for a simulation of 80 perfect trials, with random group sizes, and each patient's outcome randomly sampled (10% control event probability, and a 30% effect size for treatment). Analysis shows no asymmetry (p > 0.05). In plot B, we add a single typical variation in COVID-19 treatment trials — treatment delay. Consider that efficacy varies from 90% for treatment within 24 hours, reducing to 10% when treatment is delayed 3 days. In plot B, each trial's treatment delay is randomly selected. Analysis now shows highly significant asymmetry, p < 0.0001, with six variants of Egger's test all showing $p < 0.05^{85-92}$. Note that these tests fail even though treatment delay is uniformly distributed. In reality treatment delay is more complex — each trial has a different distribution of delays across patients, and the distribution across trials may be biased (e.g., late treatment trials may be more common). Similarly, many other variations in trials may produce asymmetry, including dose, administration, duration of treatment, differences in SOC, comorbidities, age, variants, and bias in design, implementation, analysis, and reporting.



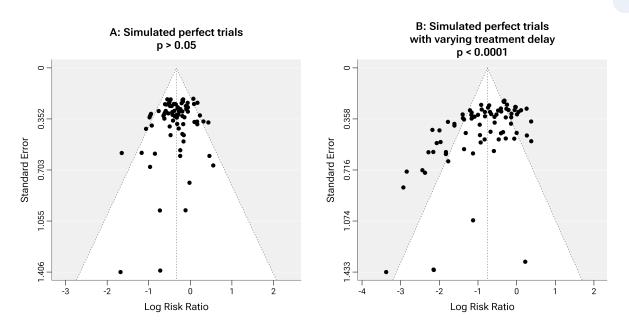


Figure 24. Example funnel plot analysis for simulated perfect trials.

Conflicts of interest

Pharmaceutical drug trials often have conflicts of interest whereby sponsors or trial staff have a financial interest in the outcome being positive. Montelukast for COVID-19 lacks this because it is off-patent, has multiple manufacturers, and is very low cost. In contrast, most COVID-19 montelukast trials have been run by physicians on the front lines with the primary goal of finding the best methods to save human lives and minimize the collateral damage caused by COVID-19. While pharmaceutical companies are careful to run trials under optimal conditions (for example, restricting patients to those most likely to benefit, only including patients that can be treated soon after onset when necessary, and ensuring accurate dosing), not all montelukast trials represent the optimal conditions for efficacy.

Limitations

Summary statistics from meta analysis necessarily lose information. As with all meta analyses, studies are heterogeneous, with differences in treatment delay, treatment regimen, patient demographics, variants, conflicts of interest, standard of care, and other factors. We provide analyses for specific outcomes and by treatment delay, and we aim to identify key characteristics in the forest plots and summaries. Results should be viewed in the context of study characteristics.

Some analyses classify treatment based on early or late administration, as done here, while others distinguish between mild, moderate, and severe cases. Viral load does not indicate degree of symptoms — for example patients may have a high viral load while being asymptomatic. With regard to treatments that have antiviral properties, timing of treatment is critical — late administration may be less helpful regardless of severity.

Details of treatment delay per patient is often not available. For example, a study may treat 90% of patients relatively early, but the events driving the outcome may come from 10% of patients treated very late. Our 5 day cutoff for early treatment may be too conservative, 5 days may be too late in many cases.

Comparison across treatments is confounded by differences in the studies performed, for example dose, variants, and conflicts of interest. Trials with conflicts of interest may use designs better suited to the preferred outcome.

In some cases, the most serious outcome has very few events, resulting in lower confidence results being used in pooled analysis, however the method is simpler and more transparent. This is less critical as the number of studies increases. Restriction to outcomes with sufficient power may be beneficial in pooled analysis and improve accuracy when there are few studies, however we maintain our pre-specified method to avoid any retrospective changes.



Studies show that combinations of treatments can be highly synergistic and may result in many times greater efficacy than individual treatments alone ⁶³⁻⁷⁹. Therefore standard of care may be critical and benefits may diminish or disappear if standard of care does not include certain treatments.

This real-time analysis is constantly updated based on submissions. Accuracy benefits from widespread review and submission of updates and corrections from reviewers. Less popular treatments may receive fewer reviews.

No treatment or intervention is 100% available and effective for all current and future variants. Efficacy may vary significantly with different variants and within different populations. All treatments have potential side effects. Propensity to experience side effects may be predicted in advance by qualified physicians. We do not provide medical advice. Before taking any medication, consult a qualified physician who can compare all options, provide personalized advice, and provide details of risks and benefits based on individual medical history and situations.

Notes

1 of 9 studies combine treatments. The results of montelukast alone may differ. None of the RCTs use combined treatment. Currently all studies are peer-reviewed.

Reviews

Multiple reviews cover montelukast for COVID-19, presenting additional background on mechanisms and related results, including ^{93,94}.

Other studies

Additional preclinical or review papers suggesting potential benefits of montelukast for COVID-19 include¹⁰⁴⁻¹¹⁹. We have not reviewed these studies in detail.

Perspective

Results compared with other treatments

SARS-CoV-2 infection and replication involves a complex interplay of 100+ host and viral proteins and other factors²⁴⁻³¹, providing many therapeutic targets. Over 9,000 compounds have been predicted to reduce COVID-19 risk³², either by directly minimizing infection or replication, by supporting immune system function, or by minimizing secondary complications. Figure 25 shows an overview of the results for montelukast in the context of multiple COVID-19 treatments, and Figure 26 shows a plot of efficacy vs. cost for COVID-19 treatments.



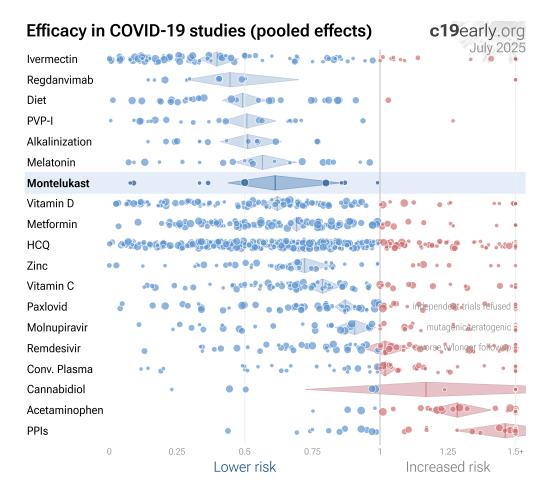


Figure 25. Scatter plot showing results within the context of multiple COVID-19 treatments. Diamonds shows the results of random effects meta-analysis. 0.6% of 9,000+ proposed treatments show efficacy¹²⁰.

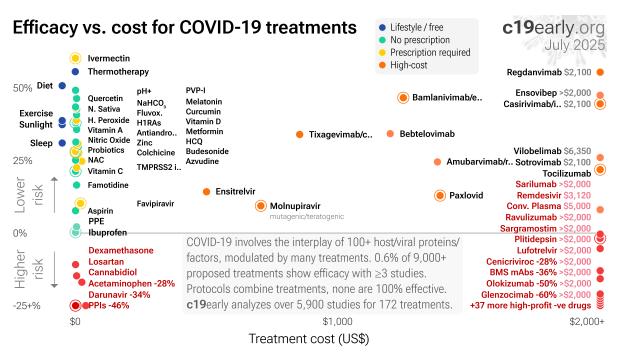


Figure 26. Efficacy vs. cost for COVID-19 treatments.



Conclusion

Studies to date show that montelukast is an effective treatment for COVID-19. Significantly lower risk is seen for hospitalization and cases. 4 studies from 4 independent teams in 4 countries show significant benefit. Meta analysis using the most serious outcome reported shows 39% [14-56%] lower risk. Results are similar for Randomized Controlled Trials and higher quality studies.

Montelukast has a boxed warning for neuropsychiatric side effects³.

Currently there is limited data, with only 37 control events for the most serious outcome in trials to date.

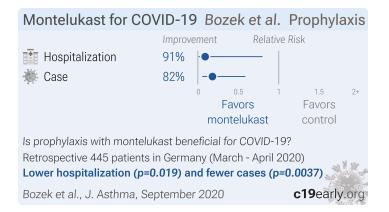
Study Notes

Alhmoud



Retrospective 616 COVID-19 patients with asthma in Qatar showing no significant difference in hospitalization risk with montelukast use.

Bozek



Retrospective 445 elderly patients with severe asthma showing reduced risk of COVID-19 infection with montelukast treatment.

Cordero

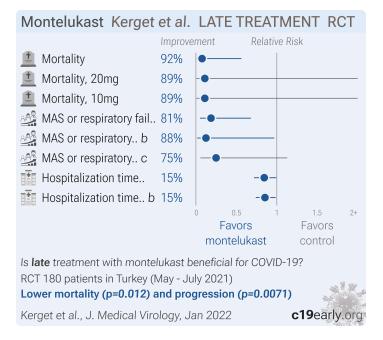
Estimated 284 patient montelukast late treatment RCT with results not reported over 1.5 years after estimated completion.



Durdagi

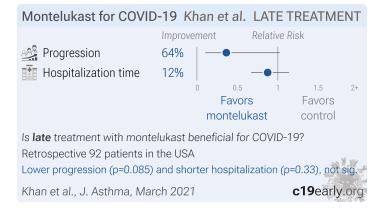
Estimated 380 patient montelukast early treatment RCT with results not reported over 3 years after estimated completion.

Kerget



RCT 180 hospitalized COVID-19 patients in Turkey showing faster reduction in inflammatory markers, improved pulmonary function, and lower rates of macrophage activation syndrome, respiratory failure and mortality with montelukast treatment (10mg or 20mg daily) in addition to standard care. The higher dose of 20mg daily showed greater improvement in pulmonary function compared to 10mg daily. There was no mortality in the montelukast groups compared to 6.7% mortality with standard care alone.

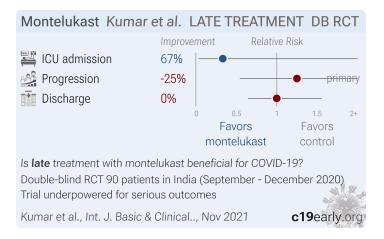
Khan



Retrospective 92 hospitalized patients showing lower clinical deterioration with montelukast treatment, without statistical significance in multivariable analysis. The treatment group was older.

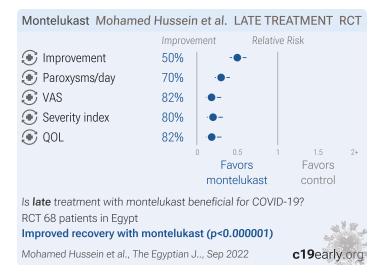


Kumar



RCT 90 mild to moderate COVID-19 patients showing no significant differences with montelukast treatment.

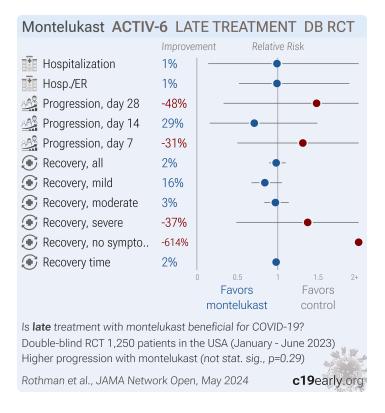
Mohamed Hussein



RCT 68 post-COVID-19 outpatients showing improvement in cough severity measures with montelukast treatment. The montelukast group had a greater reduction in number of cough paroxysms per day, cough severity visual analog scale, cough severity index, and improved cough quality of life scores compared to the control group. The montelukast group also had a shorter duration of cough.



Rothman



RCT 1,250 outpatients with mild to moderate COVID-19 showing no significant difference in time to sustained recovery with montelukast treatment. There were no deaths and only 2 hospitalizations in each group.

Notably, results were better with patients that had mild COVID-19 at baseline compared to moderate/severe cases, and overall efficacy is reduced by poor results with extremely late treatment 9 days after onset, and with patients that had no symptoms at baseline.

Authors note the treatment drug was voluntarily recalled and replaced from another source but do not report why the drug was recalled. Authors describe previous research testing 10mg and 20mg doses, noting that only 20mg showed improved pulmonary function testing, however authors do not indicate why they chose to test the lower dose for COVID-19.

It is unclear why authors only report all-cause hospitalization and urgent care and do not report COVID-19 specific outcomes. Given the low rate of urgent care visits and hospitalization, and the expected baseline frequency of these events independent of COVID-19, most or all of these events may be unrelated to COVID-19.

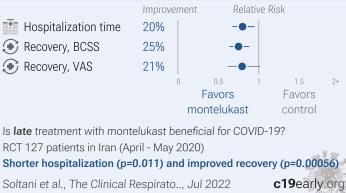
Authors note that previous research showed improvements specifically for cough, and authors collected cough data, however no results for cough are reported.

ACTIV trial authors have reported a number of issues that may affect the reliability of the results in ACTIV trials including participant fraud ¹²¹, biased participant demographics ¹²², resource issues that may have led to protocol deviations ¹²², differences in trial design including inconsistent inclusion/exclusion criteria ¹²², participant self-selection bias ^{121,122}, underrepresentation of older patients due to web-based recruitment ¹²², changes in treatment and public health policies during trials ¹²², treatment delay determination from shipping logs and delivery that may not be directly to the patient ¹²¹, variable placebo responses (e.g., oral vs. inhaled) ¹²³, logistical challenges maintaining blinding ¹²³, errors from complex data collection systems ¹²³, unplanned design changes including endpoint changes ¹²³, and inconsistent SoC across trial sites and time periods ¹²³.



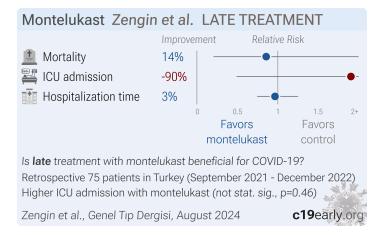
Soltani

Montelukast Soltani et al. LATE TREATMENT RCT



RCT 180 hospitalized COVID-19 patients showing improved cough symptoms and shorter hospitalization with montelukast/gabapentin compared to gabapentin. For gabapentin vs. dextromethorphan there was no significant difference in hospitalization and reduced improvement in cough symptoms.

Zengin



Retrospective 75 hospitalized COVID-19 patients over 60 in Turkey showing no significant differences with montelukast treatment.

Appendix 1. Methods and Data

We perform ongoing searches of PubMed, medRxiv, Europe PMC, ClinicalTrials.gov, The Cochrane Library, Google Scholar, Research Square, ScienceDirect, Oxford University Press, the reference lists of other studies and metaanalyses, and submissions to the site c19early.org. Search terms are montelukast and COVID-19 or SARS-CoV-2. Automated searches are performed twice daily, with all matches reviewed for inclusion. All studies regarding the use of montelukast for COVID-19 that report a comparison with a control group are included in the main analysis. Sensitivity analysis is performed, excluding studies with major issues, epidemiological studies, and studies with minimal available information. Studies with major unexplained data issues, for example major outcome data that is impossible to be correct with no response from the authors, are excluded. This is a living analysis and is updated regularly.

We extracted effect sizes and associated data from all studies. If studies report multiple kinds of effects then the most serious outcome is used in pooled analysis, while other outcomes are included in the outcome specific analyses. For example, if effects for mortality and cases are reported then they are both used in specific outcome analyses, while mortality is used for pooled analysis. If symptomatic results are reported at multiple times, we use the latest time, for



example if mortality results are provided at 14 days and 28 days, the results at 28 days have preference. Mortality alone is preferred over combined outcomes. Outcomes with zero events in both arms are not used, the next most serious outcome with one or more events is used. For example, in low-risk populations with no mortality, a reduction in mortality with treatment is not possible, however a reduction in hospitalization, for example, is still valuable. Clinical outcomes are considered more important than viral outcomes. When basically all patients recover in both treatment and control groups, preference for viral clearance and recovery is given to results mid-recovery where available. After most or all patients have recovered there is little or no room for an effective treatment to do better, however faster recovery is valuable. An IPD metaanalysis confirms that intermediate viral load reduction is more closely associated with hospitalization/death than

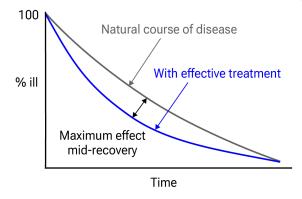


Figure 27. Mid-recovery results can more accurately reflect efficacy when almost all patients recover. *Mateja* et al. confirm that intermediate viral load results more accurately reflect hospitalization/death.

later viral load reduction ¹²⁴. If only individual symptom data is available, the most serious symptom has priority, for example difficulty breathing or low SpO_2 is more important than cough. When results provide an odds ratio, we compute the relative risk when possible, or convert to a relative risk according to *Zhang et al.* Reported confidence intervals and *p*-values are used when available, and adjusted values are used when provided. If multiple types of adjustments are reported propensity score matching and multivariable regression has preference over propensity score matching or weighting, which has preference over multivariable regression. Adjusted results have preference over unadjusted results for a more serious outcome when the adjustments significantly alter results. When needed, conversion between reported *p*-values and confidence intervals followed *Altman*, *Altman* (*B*), and Fisher's exact test was used to calculate *p*-values for event data. If continuity correction for zero values is required, we use the reciprocal of the opposite arm with the sum of the correction factors equal to 1¹²⁸. Results are expressed with RR < 1.0 favoring treatment, and using the risk of a negative outcome when applicable (for example, the risk of death rather than the risk of survival). If studies only report relative continuous values such as relative times, the ratio of the time for the treatment group versus the time for the control group is used. Calculations are done in Python (3.13.5) with scipy (1.16.0), pythonmeta (1.26), numpy (2.3.1), statsmodels (0.14.4), and plotly (6.2.0).

Forest plots are computed using PythonMeta¹²⁹ with the DerSimonian and Laird random effects model (the fixed effect assumption is not plausible in this case) and inverse variance weighting. Results are presented with 95% confidence intervals. Heterogeneity among studies was assessed using the I^2 statistic. Mixed-effects meta-regression results are computed with R (4.4.0) using the metafor (4.6-0) and rms (6.8-0) packages, and using the most serious sufficiently powered outcome. For all statistical tests, a *p*-value less than 0.05 was considered statistically significant. Grobid 0.8.2 is used to parse PDF documents.

We have classified studies as early treatment if most patients are not already at a severe stage at the time of treatment (for example based on oxygen status or lung involvement), and treatment started within 5 days of the onset of symptoms. If studies contain a mix of early treatment and late treatment patients, we consider the treatment time of patients contributing most to the events (for example, consider a study where most patients are treated early but late treatment patients are included, and all mortality events were observed with late treatment patients). We note that a shorter time may be preferable. Antivirals are typically only considered effective when used within a shorter timeframe, for example 0-36 or 0-48 hours for oseltamivir, with longer delays not being effective^{48,49}.

We received no funding, this research is done in our spare time. We have no affiliations with any pharmaceutical companies or political parties.

A summary of study results is below. Please submit updates and corrections at https://c19early.org/mkmeta.html.

Early treatment

Effect extraction follows pre-specified rules as detailed above and gives priority to more serious outcomes. For pooled analyses, the first (most serious) outcome is used, which may differ from the effect a paper focuses on. Other outcomes are used in outcome specific analyses.



Late treatment

Effect extraction follows pre-specified rules as detailed above and gives priority to more serious outcomes. For pooled analyses, the first (most serious) outcome is used, which may differ from the effect a paper focuses on. Other outcomes are used in outcome specific analyses.

Cordero, 8/31/2023, Double Blind Randomized Controlled Trial, placebo-controlled, Spain, trial NCT04695704 (history) (E-SPERANZA).	Estimated 284 patient RCT with results unknown and over 1.5 years late.				
Kerget, 1/4/2022, Randomized Controlled Trial, Turkey, peer-reviewed, mean age 54.6, 4 authors, study period May 2021 - July 2021, trial NCT05094596 (history).	risk of death, 92.3% lower, RR 0.08, $p = 0.01$, treatment 0 of (0.0%), control 4 of 60 (6.7%), NNT 15, relative risk is not 0 because of continuity correction due to zero events (with reciprocal of the contrasting arm).				
	risk of death, 88.9% lower, RR 0.11, $p = 0.12$, treatment 0 of 60 (0.0%), control 4 of 60 (6.7%), NNT 15, relative risk is not 0 because of continuity correction due to zero events (with reciprocal of the contrasting arm), 20mg.				
	risk of death, 88.9% lower, RR 0.11, $p = 0.12$, treatment 0 of 60 (0.0%), control 4 of 60 (6.7%), NNT 15, relative risk is not 0 because of continuity correction due to zero events (with reciprocal of the contrasting arm), 10mg.				
	MAS or respiratory failure, 81.2% lower, RR 0.19, <i>p</i> = 0.007, treatment 3 of 120 (2.5%), control 8 of 60 (13.3%), NNT 9.2.				
	MAS or respiratory failure, 87.5% lower, RR 0.12, <i>p</i> = 0.03, treatment 1 of 60 (1.7%), control 8 of 60 (13.3%), NNT 8.6, 20mg.				
	MAS or respiratory failure, 75.0% lower, RR 0.25, <i>p</i> = 0.09, treatment 2 of 60 (3.3%), control 8 of 60 (13.3%), NNT 10.0, 10mg.				
	hospitalization time, 15.5% lower, relative time 0.85, $p = 0.04$, treatment mean 9.3 (±3.6) n=60, control mean 11.0 (±5.3) n=60, 20mg.				
	hospitalization time, 14.5% lower, relative time 0.85, $p = 0.03$, treatment mean 9.4 (±2.1) n=60, control mean 11.0 (±5.3) n=60, 10mg.				
Khan, 3/4/2021, retrospective, USA, peer-reviewed, 16 authors.	risk of progression, 63.5% lower, RR 0.36, $p = 0.09$, treatment 3 of 30 (10.0%), control 20 of 62 (32.3%), NNT 4.5, adjusted per study, odds ratio converted to relative risk, multivariable.				
	hospitalization time, 12.5% lower, relative time 0.88, p = 0.33, treatment median 7.0 IQR 6.5 n=30, control median 8.0 IQR 6.0 n=62.				
Kumar (B), 11/22/2021, Double Blind Randomized Controlled Trial, placebo-controlled, India, peer-	risk of ICU admission, 66.7% lower, RR 0.33, <i>p</i> = 0.62, treatmen 1 of 45 (2.2%), control 3 of 45 (6.7%), NNT 23.				
reviewed, mean age 45.0, 10 authors, study period 1 September, 2020 - 31 December, 2020, average treatment delay 5.8 days.	risk of progression, 25.0% higher, RR 1.25, $p = 0.79$, treatment 10 of 45 (22.2%), control 8 of 45 (17.8%), primary outcome.				



	risk of no hospital discharge, no change, RR 1.00, <i>p</i> = 1.00, treatment 21 of 45 (46.7%), control 21 of 45 (46.7%).				
Lima-Morales, 2/10/2021, prospective, Mexico, peer-reviewed, 10 authors, average treatment delay 7.2 days, this trial uses multiple treatments in the	risk of death, 77.7% lower, RR 0.22, <i>p</i> < 0.001, treatment 15 of 481 (3.1%), control 52 of 287 (18.1%), NNT 6.7, adjusted per study, odds ratio converted to relative risk, multivariate.				
treatment arm (combined with azithromycin, montelukast, and aspirin) - results of individual treatments may vary, excluded: combined	risk of mechanical ventilation, 51.9% lower, RR 0.48, p = 0.15, treatment 8 of 434 (1.8%), control 11 of 287 (3.8%), NNT 50.				
treatments may contribute more to the effect seen.	risk of hospitalization, 67.4% lower, RR 0.33, <i>p</i> < 0.001, treatment 44 of 481 (9.1%), control 89 of 287 (31.0%), NNT 4.6, adjusted per study, odds ratio converted to relative risk, multivariate.				
	risk of no recovery, 58.6% lower, RR 0.41, $p < 0.001$, treatment 75 of 481 (15.6%), control 118 of 287 (41.1%), NNT 3.9, adjusted per study, inverted to make RR<1 favor treatment, odds ratio converted to relative risk, recovery at day 14 after symptoms, multivariate.				
Mohamed Hussein, 9/15/2022, Randomized Controlled Trial, Egypt, peer-reviewed, mean age 43.0, 7 authors, post-COVID cough.	improvement, 50.0% lower, relative time 0.50, $p < 0.001$, treatment mean 5.0 (±1.4) n=32, control mean 10.0 (±1.5) n=36.				
	paroxysms/day, 70.0% lower, relative time 0.30, $p < 0.001$, treatment mean 3.0 (±1.2) n=32, control mean 10.0 (±4.1) n=36.				
	VAS, 81.8% lower, relative time 0.18, <i>p</i> < 0.001, treatment mean 12.0 (±6.0) n=32, control mean 66.0 (±12.0) n=36.				
	severity index, 80.0% lower, relative time 0.20, <i>p</i> < 0.001, treatment mean 4.0 (±1.1) n=32, control mean 20.0 (±5.0) n=36.				
	QOL, 81.6% lower, relative time 0.18, <i>p</i> < 0.001, treatment mean 18.0 (±2.5) n=32, control mean 98.0 (±2.0) n=36.				
Rothman, 5/18/2024, Double Blind Randomized Controlled Trial, placebo-controlled, USA, peer-	risk of hospitalization, 1.0% lower, RR 0.99, <i>p</i> = 1.00, treatment 2 of 628 (0.3%), control 2 of 622 (0.3%), NNT 32551.				
reviewed, median age 53.0, 32 authors, study period 27 January, 2023 - 23 June, 2023, trial NCT04885530 (history) (ACTIV-6).	hosp./ER, 1.0% lower, RR 0.99, <i>p</i> = 1.00, treatment 18 of 628 (2.9%), control 18 of 622 (2.9%), NNT 3617.				
	risk of progression, 48.0% higher, OR 1.48, <i>p</i> = 0.29, clinical progression, day 28, RR approximated with OR.				
	risk of progression, 29.0% lower, OR 0.71, $p = 0.82$, clinical progression, day 14, RR approximated with OR.				
	risk of progression, 31.0% higher, OR 1.31, $p = 0.27$, clinical progression, day 7, RR approximated with OR.				
	risk of no recovery, 2.0% lower, HR 0.98, $p = 0.72$, treatment 628, control 622, inverted to make HR<1 favor treatment, all patients.				
	risk of no recovery, 16.0% lower, HR 0.84, $p = 0.12$, treatment 186, control 183, inverted to make HR<1 favor treatment, patients with mild symptoms on day 1.				
	risk of no recovery, 2.9% lower, HR 0.97, $p = 0.72$, treatment 341, control 337, inverted to make HR<1 favor treatment, patients with moderate symptoms on day 1.				



	risk of no recovery, 37.0% higher, HR 1.37, $p = 0.56$, treatment 10, control 13, inverted to make HR<1 favor treatment, patients with severe symptoms on day 1.
	risk of no recovery, 614.3% higher, HR 7.14, <i>p</i> < 0.001, treatment 186, control 183, inverted to make HR<1 favor treatment, patients with no symptoms on day 1.
	recovery time, 2.0% lower, relative time 0.98, $p = 0.07$, treatment mean 11.77 (±2.49) n=628, control mean 12.01 (±2.16) n=622.
Soltani, 7/31/2022, Randomized Controlled Trial, Iran, peer-reviewed, mean age 56.8, 6 authors, study period April 2020 - May 2020.	hospitalization time, 20.0% lower, relative time 0.80, $p = 0.01$, treatment median 8.0 IQR 3.0 n=51, control median 10.0 IQR 7.0 n=76.
	risk of no recovery, 25.0% lower, RR 0.75, <i>p</i> < 0.001, treatment mean 1.96 (±0.69) n=51, control mean 1.47 (±0.81) n=76, relative BCSS improvement, GPT/MTL vs. GPT.
	risk of no recovery, 20.6% lower, RR 0.79, <i>p</i> = 0.07, treatment mean 1.8 (±1.11) n=51, control mean 1.43 (±1.13) n=76, relative VAS improvement, GPT/MTL vs. GPT.
Zengin, 8/5/2024, retrospective, Turkey, peer- reviewed, 9 authors, study period September 2021 -	risk of death, 14.3% lower, RR 0.86, p = 1.00, treatment 3 of 35 (8.6%), control 4 of 40 (10.0%), NNT 70.
December 2022, excluded in exclusion analyses: unadjusted results with minimal group details.	risk of ICU admission, 90.5% higher, RR 1.90, <i>p</i> = 0.46, treatment 5 of 35 (14.3%), control 3 of 40 (7.5%).
	hospitalization time, 3.4% lower, relative time 0.97, $p = 0.81$, treatment mean 10.51 (±5.44) n=35, control mean 10.88 (±7.24) n=40.

Prophylaxis

Effect extraction follows pre-specified rules as detailed above and gives priority to more serious outcomes. For pooled analyses, the first (most serious) outcome is used, which may differ from the effect a paper focuses on. Other outcomes are used in outcome specific analyses.

Alhmoud, 9/23/2023, retrospective, Qatar, peer-	risk of hospitalization, 13.0% lower, OR 0.87, <i>p</i> = 0.61,			
reviewed, median age 44.0, 10 authors, study	treatment 111, control 505, adjusted per study, multivariable, RR			
period 10 March, 2020 - 10 August, 2020.	approximated with OR.			
Bozek, 9/17/2020, retrospective, Germany, peer-	risk of hospitalization, 91.0% lower, RR 0.09, <i>p</i> = 0.02,			
reviewed, 2 authors, study period March 2020 -	treatment 1 of 327 (0.3%), control 4 of 118 (3.4%), NNT 32.			
April 2020.	risk of case, 82.0% lower, RR 0.18, <i>p</i> = 0.004, treatment 4 of 327 (1.2%), control 8 of 118 (6.8%), NNT 18.			

Supplementary Data

Supplementary Data



Footnotes

- a. Viral infection and replication involves attachment, entry, uncoating and release, genome replication and transcription, translation and protein processing, assembly and budding, and release. Each step can be disrupted by therapeutics.
- b. The trimeric spike (S) protein is a glycoprotein that mediates viral entry by binding to the host ACE2 receptor, is critical for SARS-CoV-2's ability to infect host cells, and is a target of neutralizing antibodies. Inhibition of the spike protein prevents viral attachment, halting infection at the earliest stage.
- c. The receptor binding domain is a specific region of the spike protein that binds ACE2 and is a major target of neutralizing antibodies. Focusing on the precise binding site allows highly specific disruption of viral attachment with reduced potential for off-target effects.
- d. The main protease or M^{pro}, also known as 3CL^{pro} or nsp5, is a cysteine protease that cleaves viral polyproteins into functional units needed for replication. Inhibiting M^{pro} disrupts the SARS-CoV-2 lifecycle within the host cell, preventing the creation of new copies.
- e. RNA-dependent RNA polymerase (RdRp), also called nsp12, is the core enzyme of the viral replicase-transcriptase complex that copies the positive-sense viral RNA genome into negative-sense templates for progeny RNA synthesis. Inhibiting RdRp blocks viral genome replication and transcription.
- f. The papain-like protease (PLpro) has multiple functions including cleaving viral polyproteins and suppressing the host immune response by deubiquitination and delSGylation of host proteins. Inhibiting PLpro may block viral replication and help restore normal immune responses.
- g. The nucleocapsid (N) protein binds and encapsulates the viral genome by coating the viral RNA. N enables formation and release of infectious virions and plays additional roles in viral replication and pathogenesis. N is also an immunodominant antigen used in diagnostic assays.
- h. The helicase, or nsp13, protein unwinds the double-stranded viral RNA, a crucial step in replication and transcription. Inhibition may prevent viral genome replication and the creation of new virus components.

References

- Cordero et al., Double-blind Randomized Clinical Trial, Placebo-controlled to Assess the Efficacy of Montelukast in Mild-moderate Respiratory Symptoms in Patients With Long-COVID-19: E-SPERANZA COVID-19 PROJECT, NCT04695704, clinicaltrials.gov/study/NCT04695704.
- Durdagi et al., A National, Multi-Center, Open-Label, Three-Arm, Phase II Study to Investigate the Effect of Montelukast Between Emergency Room Visits and Hospitalizations in COVID-19 Pneumonia in Comparison With Standard Treatment, NCT04718285, clinicaltrials.gov/study/NCT04718285.
- 3. fda.gov,

www.fda.gov/drugs/drug-safety-and-availability/fda-requires-box ed-warning-about-serious-mental-health-side-effects-asthma-an d-allergy-drug.

- Ryu et al., Fibrin drives thromboinflammation and neuropathology in COVID-19, Nature, doi:10.1038/s41586-024-07873-4.
- Rong et al., Persistence of spike protein at the skull-meningesbrain axis may contribute to the neurological sequelae of COVID-19, Cell Host & Microbe, doi:10.1016/j.chom.2024.11.007.
- Yang et al., SARS-CoV-2 infection causes dopaminergic neuron senescence, Cell Stem Cell, doi:10.1016/j.stem.2023.12.012.

- 7. **Scardua-Silva** et al., Microstructural brain abnormalities, fatigue, and cognitive dysfunction after mild COVID-19, Scientific Reports, doi:10.1038/s41598-024-52005-7.
- 8. **Hampshire** et al., Cognition and Memory after Covid-19 in a Large Community Sample, New England Journal of Medicine, doi:10.1056/NEJMoa2311330.
- Duloquin et al., Is COVID-19 Infection a Multiorganic Disease? Focus on Extrapulmonary Involvement of SARS-CoV-2, Journal of Clinical Medicine, doi:10.3390/jcm13051397.
- Sodagar et al., Pathological Features and Neuroinflammatory Mechanisms of SARS-CoV-2 in the Brain and Potential Therapeutic Approaches, Biomolecules, doi:10.3390/biom12070971.
- Sagar et al., COVID-19-associated cerebral microbleeds in the general population, Brain Communications, doi:10.1093/braincomms/fcae127.
- Verma et al., Persistent Neurological Deficits in Mouse PASC Reveal Antiviral Drug Limitations, bioRxiv, doi:10.1101/2024.06.02.596989.
- Panagea et al., Neurocognitive Impairment in Long COVID: A Systematic Review, Archives of Clinical Neuropsychology, doi:10.1093/arclin/acae042.
- Ariza et al., COVID-19: Unveiling the Neuropsychiatric Maze — From Acute to Long-Term Manifestations, Biomedicines, doi:10.3390/biomedicines12061147.



- Vashisht et al., Neurological Complications of COVID-19: Unraveling the Pathophysiological Underpinnings and Therapeutic Implications, Viruses, doi:10.3390/v16081183.
- 16. Ahmad et al., Neurological Complications and Outcomes in Critically III Patients With COVID-19: Results From International Neurological Study Group From the COVID-19 Critical Care Consortium, The Neurohospitalist, doi:10.1177/19418744241292487.
- 17. **Wang** et al., SARS-CoV-2 membrane protein induces neurodegeneration via affecting Golgi-mitochondria interaction, Translational Neurodegeneration, doi:10.1186/s40035-024-00458-1.
- Eberhardt et al., SARS-CoV-2 infection triggers proatherogenic inflammatory responses in human coronary vessels, Nature Cardiovascular Research, doi:10.1038/s44161-023-00336-5.
- Van Tin et al., Spike Protein of SARS-CoV-2 Activates Cardiac Fibrogenesis through NLRP3 Inflammasomes and NF-κB Signaling, Cells, doi:10.3390/cells13161331.
- Borka Balas et al., COVID-19 and Cardiac Implications Still a Mystery in Clinical Practice, Reviews in Cardiovascular Medicine, doi:10.31083/j.rcm2405125.
- AlTaweel et al., An In-Depth Insight into Clinical, Cellular and Molecular Factors in COVID19-Associated Cardiovascular Ailments for Identifying Novel Disease Biomarkers, Drug Targets and Clinical Management Strategies, Archives of Microbiology & Immunology, doi:10.26502/ami.936500177.
- 22. Saha et al., COVID-19 beyond the lungs: Unraveling its vascular impact and cardiovascular complications mechanisms and therapeutic implications, Science Progress, doi:10.1177/00368504251322069.
- 23. **Trender** et al., Changes in memory and cognition during the SARS-CoV-2 human challenge study, eClinicalMedicine, doi:10.1016/j.eclinm.2024.102842.
- 24. **Dugied** et al., Multimodal SARS-CoV-2 interactome sketches the virus-host spatial organization, Communications Biology, doi:10.1038/s42003-025-07933-z.
- Malone et al., Structures and functions of coronavirus replication-transcription complexes and their relevance for SARS-CoV-2 drug design, Nature Reviews Molecular Cell Biology, doi:10.1038/s41580-021-00432-z.
- 26. **Murigneux** et al., Proteomic analysis of SARS-CoV-2 particles unveils a key role of G3BP proteins in viral assembly, Nature Communications, doi:10.1038/s41467-024-44958-0.
- 27. Lv et al., Host proviral and antiviral factors for SARS-CoV-2, Virus Genes, doi:10.1007/s11262-021-01869-2.
- Lui et al., Nsp1 facilitates SARS-CoV-2 replication through calcineurin-NFAT signaling, Virology, doi:10.1128/mbio.00392-24.
- Niarakis et al., Drug-target identification in COVID-19 disease mechanisms using computational systems biology approaches, Frontiers in Immunology, doi:10.3389/fimmu.2023.1282859.
- Katiyar et al., SARS-CoV-2 Assembly: Gaining Infectivity and Beyond, Viruses, doi:10.3390/v16111648.

- Wu et al., Decoding the genome of SARS-CoV-2: a pathway to drug development through translation inhibition, RNA Biology, doi:10.1080/15476286.2024.2433830.
- 32. c19early.org, c19early.org/treatments.html.
- Haque et al., Exploring potential therapeutic candidates against COVID-19: a molecular docking study, Discover Molecules, doi:10.1007/s44345-024-00005-5.
- Mulgaonkar et al., Montelukast and Telmisartan as Inhibitors of SARS-CoV-2 Omicron Variant, Pharmaceutics, doi:10.3390/pharmaceutics15071891.
- 35. Hamdan et al., In silico Evaluation of H1-Antihistamine as Potential Inhibitors of SARS-CoV-2 RNA-dependent RNA Polymerase: Repurposing Study of COVID-19 Therapy, Turkish Journal of Pharmaceutical Sciences, doi:10.4274/tjps.galenos.2024.49768.
- Camera et al., Montelukast Inhibits Platelet Activation Induced by Plasma From COVID-19 Patients, Frontiers in Pharmacology, doi:10.3389/fphar.2022.784214.
- Jadad et al., Randomized Controlled Trials: Questions, Answers, and Musings, Second Edition, doi:10.1002/9780470691922.
- Gøtzsche, P., Bias in double-blind trials, Doctoral Thesis, University of Copenhagen, www.scientificfreedom.dk/2023/05/16/bias-in-double-blind-trial s-doctoral-thesis/.
- 39. **Als-Nielsen** et al., Association of Funding and Conclusions in Randomized Drug Trials, JAMA, doi:10.1001/jama.290.7.921.
- 40. **c19early.org (B)**, c19early.org/mksupp.html#fig_rctobs.
- 41. **Concato** et al., NEJM, 342:1887-1892, doi:10.1056/NEJM200006223422507.
- 42. **Anglemyer** et al., Healthcare outcomes assessed with observational study designs compared with those assessed in randomized trials, Cochrane Database of Systematic Reviews 2014, Issue 4, doi:10.1002/14651858.MR000034.pub2.
- 43. c19early.org (C), c19early.org/rctobs.html.
- Lee et al., Analysis of Overall Level of Evidence Behind Infectious Diseases Society of America Practice Guidelines, Arch Intern Med., 2011, 171:1, 18-22, doi:10.1001/archinternmed.2010.482.
- Deaton et al., Understanding and misunderstanding randomized controlled trials, Social Science & Medicine, 210, doi:10.1016/j.socscimed.2017.12.005.
- 46. **Nichol** et al., Challenging issues in randomised controlled trials, Injury, 2010, doi: 10.1016/j.injury.2010.03.033, www.injuryjournal.com/article/S0020-1383(10)00233-0/fulltex t.
- Zengin et al., The Effect of Montelukast Treatment on Elderly Patients Diagnosed with COVID-19, Genel Tıp Dergisi, doi:10.54005/geneltip.1352153.
- Treanor et al., Efficacy and Safety of the Oral Neuraminidase Inhibitor Oseltamivir in Treating Acute Influenza: A Randomized Controlled Trial, JAMA, 2000, 283:8, 1016-1024, doi:10.1001/jama.283.8.1016.



- McLean et al., Impact of Late Oseltamivir Treatment on Influenza Symptoms in the Outpatient Setting: Results of a Randomized Trial, Open Forum Infect. Dis. September 2015, 2:3, doi:10.1093/ofid/ofv100.
- Ikematsu et al., Baloxavir Marboxil for Prophylaxis against Influenza in Household Contacts, New England Journal of Medicine, doi:10.1056/NEJMoa1915341.
- Hayden et al., Baloxavir Marboxil for Uncomplicated Influenza in Adults and Adolescents, New England Journal of Medicine, doi:10.1056/NEJMoa1716197.
- 52. **Kumar** et al., Combining baloxavir marboxil with standard-ofcare neuraminidase inhibitor in patients hospitalised with severe influenza (FLAGSTONE): a randomised, parallel-group, double-blind, placebo-controlled, superiority trial, The Lancet Infectious Diseases, doi:10.1016/S1473-3099(21)00469-2.
- López-Medina et al., Effect of Ivermectin on Time to Resolution of Symptoms Among Adults With Mild COVID-19: A Randomized Clinical Trial, JAMA, doi:10.1001/jama.2021.3071.
- 54. **Korves** et al., SARS-CoV-2 Genetic Variants and Patient Factors Associated with Hospitalization Risk, medRxiv, doi:10.1101/2024.03.08.24303818.
- 55. Faria et al., Genomics and epidemiology of the P.1 SARS-CoV-2 lineage in Manaus, Brazil, Science, doi:10.1126/science.abh2644.
- 56. Nonaka et al., SARS-CoV-2 variant of concern P.1 (Gamma) infection in young and middle-aged patients admitted to the intensive care units of a single hospital in Salvador, Northeast Brazil, February 2021, International Journal of Infectious Diseases, doi:10.1016/j.ijid.2021.08.003.
- 57. **Karita** et al., Trajectory of viral load in a prospective population-based cohort with incident SARS-CoV-2 G614 infection, medRxiv, doi:10.1101/2021.08.27.21262754.
- 58. Zavascki et al., Advanced ventilatory support and mortality in hospitalized patients with COVID-19 caused by Gamma (P.1) variant of concern compared to other lineages: cohort study at a reference center in Brazil, Research Square, doi:10.21203/rs.3.rs-910467/v1.
- Willett et al., The hyper-transmissible SARS-CoV-2 Omicron variant exhibits significant antigenic change, vaccine escape and a switch in cell entry mechanism, medRxiv, doi:10.1101/2022.01.03.21268111.
- 60. Peacock et al., The SARS-CoV-2 variant, Omicron, shows rapid replication in human primary nasal epithelial cultures and efficiently uses the endosomal route of entry, bioRxiv, doi:10.1101/2021.12.31.474653.
- 61. **Williams**, T., Not All Ivermectin Is Created Equal: Comparing The Quality of 11 Different Ivermectin Sources, Do Your Own Research,

doyourownresearch.substack.com/p/not-all-ivermectin-is-create d-equal.

62. **Xu** et al., A study of impurities in the repurposed COVID-19 drug hydroxychloroquine sulfate by UHPLC-Q/TOF-MS and LC-SPE-NMR, Rapid Communications in Mass Spectrometry, doi:10.1002/rcm.9358.

- 63. Jitobaom et al., Favipiravir and Ivermectin Showed in Vitro Synergistic Antiviral Activity against SARS-CoV-2, Research Square, doi:10.21203/rs.3.rs-941811/v1.
- Jitobaom (B) et al., Synergistic anti-SARS-CoV-2 activity of repurposed anti-parasitic drug combinations, BMC Pharmacology and Toxicology, doi:10.1186/s40360-022-00580-8.
- 65. **Jeffreys** et al., Remdesivir-ivermectin combination displays synergistic interaction with improved in vitro activity against SARS-CoV-2, International Journal of Antimicrobial Agents, doi:10.1016/j.ijantimicag.2022.106542.
- 66. **Ostrov** et al., Highly Specific Sigma Receptor Ligands Exhibit Anti-Viral Properties in SARS-CoV-2 Infected Cells, Pathogens, doi:10.3390/pathogens10111514.
- Alsaidi et al., Griffithsin and Carrageenan Combination Results in Antiviral Synergy against SARS-CoV-1 and 2 in a Pseudoviral Model, Marine Drugs, doi:10.3390/md19080418.
- Andreani et al., In vitro testing of combined hydroxychloroquine and azithromycin on SARS-CoV-2 shows synergistic effect, Microbial Pathogenesis, doi:10.1016/j.micpath.2020.104228.
- De Forni et al., Synergistic drug combinations designed to fully suppress SARS-CoV-2 in the lung of COVID-19 patients, PLoS ONE, doi:10.1371/journal.pone.0276751.
- Wan et al., Synergistic inhibition effects of andrographolide and baicalin on coronavirus mechanisms by downregulation of ACE2 protein level, Scientific Reports, doi:10.1038/s41598-024-54722-5.
- 71. **Said** et al., The effect of Nigella sativa and vitamin D3 supplementation on the clinical outcome in COVID-19 patients: A randomized controlled clinical trial, Frontiers in Pharmacology, doi:10.3389/fphar.2022.1011522.
- Fiaschi et al., In Vitro Combinatorial Activity of Direct Acting Antivirals and Monoclonal Antibodies against the Ancestral B.1 and BQ.1.1 SARS-CoV-2 Viral Variants, Viruses, doi:10.3390/v16020168.
- 73. **Xing** et al., Published anti-SARS-CoV-2 in vitro hits share common mechanisms of action that synergize with antivirals, Briefings in Bioinformatics, doi:10.1093/bib/bbab249.
- Chen et al., Synergistic Inhibition of SARS-CoV-2 Replication Using Disulfiram/Ebselen and Remdesivir, ACS Pharmacology & Translational Science, doi:10.1021/acsptsci.1c00022.
- 75. **Hempel** et al., Synergistic inhibition of SARS-CoV-2 cell entry by otamixaban and covalent protease inhibitors: pre-clinical assessment of pharmacological and molecular properties, Chemical Science, doi:10.1039/D1SC01494C.
- Schultz et al., Pyrimidine inhibitors synergize with nucleoside analogues to block SARS-CoV-2, Nature, doi:10.1038/s41586-022-04482-x.
- 77. **Ohashi** et al., Potential anti-COVID-19 agents, cepharanthine and nelfinavir, and their usage for combination treatment, iScience, doi:10.1016/j.isci.2021.102367.
- Al Krad et al., The protease inhibitor Nirmatrelvir synergizes with inhibitors of GRP78 to suppress SARS-CoV-2 replication, bioRxiv, doi:10.1101/2025.03.09.642200.

- 79. **Thairu** et al., A Comparison of Ivermectin and Non Ivermectin Based Regimen for COVID-19 in Abuja: Effects on Virus Clearance, Days-to-discharge and Mortality, Journal of Pharmaceutical Research International, doi:10.9734/jpri/2022/v34i44A36328.
- 80. **Singh** et al., The relationship between viral clearance rates and disease progression in early symptomatic COVID-19: a systematic review and meta-regression analysis, Journal of Antimicrobial Chemotherapy, doi:10.1093/jac/dkae045.
- 81. **Meneguesso**, A., Médica defende tratamento precoce da Covid-19, www.youtube.com/watch?v=X5FCrIm_19U.
- 82. **Boulware**, D., Comments regarding paper rejection, twitter.com/boulware_dr/status/1311331372884205570.
- Meeus, G., Online Comment, twitter.com/gertmeeus_MD/status/1386636373889781761.
- 84. twitter.com, twitter.com/KashPrime/status/1768487878454124914.
- 85. Rothstein, H., Publication Bias in Meta-Analysis: Prevention, Assessment and Adjustments, www.wiley.com/en-ae/Publication+Bias+in+Meta+Analysis:+Pre vention,+Assessment+and+Adjustments-p-9780470870143.
- Stanley et al., Meta-regression approximations to reduce publication selection bias, Research Synthesis Methods, doi:10.1002/jrsm.1095.
- Rücker et al., Arcsine test for publication bias in metaanalyses with binary outcomes, Statistics in Medicine, doi:10.1002/sim.2971.
- Peters, J., Comparison of Two Methods to Detect Publication Bias in Meta-analysis, JAMA, doi:10.1001/jama.295.6.676.
- Moreno et al., Assessment of regression-based methods to adjust for publication bias through a comprehensive simulation study, BMC Medical Research Methodology, doi:10.1186/1471-2288-9-2.
- Macaskill et al., A comparison of methods to detect publication bias in meta-analysis, Statistics in Medicine, doi:10.1002/sim.698.
- 91. **Egger** et al., Bias in meta-analysis detected by a simple, graphical test, BMJ, doi:10.1136/bmj.315.7109.629.
- 92. **Harbord** et al., A modified test for small-study effects in metaanalyses of controlled trials with binary endpoints, Statistics in Medicine, doi:10.1002/sim.2380.
- McCarthy, M., Montelukast as a potential treatment for COVID-19, Expert Opinion on Pharmacotherapy, doi:10.1080/14656566.2023.2192866.
- 94. **Barré** et al., Montelukast Drug May Improve COVID-19 Prognosis: A Review of Evidence, Frontiers in Pharmacology, doi:10.3389/fphar.2020.01344.
- 95. **Rothman** et al., Time to Sustained Recovery Among Outpatients With COVID-19 Receiving Montelukast vs Placebo, JAMA Network Open, doi:10.1001/jamanetworkopen.2024.39332.
- Mohamed Hussein et al., Value of montelukast as a potential treatment of post-COVID-19 persistent cough: a nonrandomized controlled pilot study, The Egyptian Journal of Bronchology, doi:10.1186/s43168-022-00154-6.

- 97. **Soltani** et al., The effectiveness of gabapentin and gabapentin/montelukast combination compared with dextromethorphan in the improvement of COVID-19- related cough: A randomized, controlled clinical trial, The Clinical Respiratory Journal, doi:10.1111/crj.13529.
- Kerget et al., Effect of montelukast therapy on clinical course, pulmonary function, and mortality in patients with COVID-19, Journal of Medical Virology, doi:10.1002/jmv.27552.
- Kumar (B) et al., Efficacy of montelukast in the management of COVID-19: double blind randomized placebo controlled trial, International Journal of Basic & Clinical Pharmacology, doi:10.18203/2319-2003.ijbcp20214502.
- 100. **Khan** et al., Montelukast in hospitalized patients diagnosed with COVID-19, Journal of Asthma, doi:10.1080/02770903.2021.1881967.
- 101. Lima-Morales et al., Effectiveness of a multidrug therapy consisting of ivermectin, azithromycin, montelukast and acetylsalicylic acid to prevent hospitalization and death among ambulatory COVID-19 cases in Tlaxcala, Mexico, International Journal of Infectious Diseases, doi:10.1016/j.ijid.2021.02.014.
- 102. **Alhmoud** et al., Characteristics and outcomes of adult patients with asthma presenting with COVID-19: A comparative cohort study, Qatar Medical Journal, doi:10.5339/qmj.2023.15.
- 103. **Bozek** et al., Montelukast's ability to fight COVID-19 infection, Journal of Asthma, doi:10.1080/02770903.2020.1786112.
- 104. Luedemann et al., Montelukast is a dual-purpose inhibitor of SARS-CoV-2 infection and virus-induced IL-6 expression identified by structure-based drug repurposing, Computational and Structural Biotechnology Journal, doi:10.1016/j.csbj.2022.01.024.
- 105. Salehi-Pourmehr et al., Effect of Montelukast on Treatment of Coronavirus Pneumonia (COVID-19): A Systematic Review, Biomedical Research Bulletin, doi:10.34172/biomedrb.2023.06.
- 106. Kumar (C) et al., Advancements in the development of antivirals against SARS-Coronavirus, Frontiers in Cellular and Infection Microbiology, doi:10.3389/fcimb.2025.1520811.
- 107. **Abdollahpour** et al., An in silico Drug Repurposing Study to Inhibit the Spike Protein of SARS-CoV2, Momona Ethiopian Journal of Science, doi:10.4314/mejs.v16i2.11.
- 108. Ridha Al Fiqri et al., Basic Structure of the Pharmacophore Virtual Screening Protein 7kg7 for Candidate Therapeutic Options COVID-19, Indonesian Journal of Medical Chemistry and Bioinformatics, doi:10.7454/ijmcb.v2i2.1004.
- 109. Loucera et al., Drug repurposing for COVID-19 using machine learning and mechanistic models of signal transduction circuits related to SARS-CoV-2 infection, Signal Transduction and Targeted Therapy, doi:10.1038/s41392-020-00417-y.
- 110. **Masoudi-Sobhanzadeh** et al., Structure-based drug repurposing against COVID-19 and emerging infectious diseases: methods, resources and discoveries, Briefings in Bioinformatics, doi:10.1093/bib/bbab113.



- 111. **Malar** et al., Network analysis-guided drug repurposing strategies targeting LPAR receptor in the interplay of COVID, Alzheimer's, and diabetes, Scientific Reports, doi:10.1038/s41598-024-55013-9.
- 112. **Maffucci** et al., In Silico Drug Repurposing for SARS-CoV-2 Main Proteinase and Spike Proteins, Journal of Proteome Research, doi:10.1021/acs.jproteome.0c00383.
- 113. **Wu (B)** et al., Analysis of therapeutic targets for SARS-CoV-2 and discovery of potential drugs by computational methods, Acta Pharmaceutica Sinica B, doi:10.1016/j.apsb.2020.02.008.
- 114. **Gysi** et al., Network Medicine Framework for Identifying Drug Repurposing Opportunities for COVID-19, arXiv, doi:10.48550/arXiv.2004.07229.
- 115. **Mittal** et al., Identification of potential molecules against COVID-19 main protease through structure-guided virtual screening approach, Journal of Biomolecular Structure and Dynamics, doi:10.1080/07391102.2020.1768151.
- 116. **Tam** et al., Targeting SARS-CoV-2 Non-Structural Proteins, International Journal of Molecular Sciences, doi:10.3390/ijms241613002.
- 117. **Chen (B)** et al., Metabolic alterations upon SARS-CoV-2 infection and potential therapeutic targets against coronavirus infection, Signal Transduction and Targeted Therapy, doi:10.1038/s41392-023-01510-8.
- 118. **Mehyar**, N., Coronaviruses SARS-CoV, MERS-CoV, and SARS-CoV-2 helicase inhibitors: A systematic review of in vitro studies, Journal of Virus Eradication, doi:10.1016/j.jve.2023.100327.
- 119. **Oliver** et al., Different drug approaches to COVID-19 treatment worldwide: an update of new drugs and drugs repositioning to fight against the novel coronavirus,

Therapeutic Advances in Vaccines and Immunotherapy, doi:10.1177/25151355221144845.

- 120. c19early.org (D), c19early.org/timeline.html.
- 121. **Lindsell** et al., ACTIV-6: Operationalizing a decentralized, outpatient randomized platform trial to evaluate efficacy of repurposed medicines for COVID-19, Journal of Clinical and Translational Science, doi:10.1017/cts.2023.644.
- 122. **Wohl** et al., Engaging communities in therapeutics clinical research during pandemics: Experiences and lessons from the ACTIV COVID-19 therapeutics research initiative, Journal of Clinical and Translational Science, doi:10.1017/cts.2024.561.
- 123. Lindsell (B) et al., The statistical design and analysis of pandemic platform trials: Implications for the future, Journal of Clinical and Translational Science, doi:10.1017/cts.2024.514.
- 124. **Mateja** et al., The choice of viral load endpoint in early phase trials of COVID-19 treatments aiming to reduce 28day hospitalization and/or death, The Journal of Infectious Diseases, doi:10.1093/infdis/jiaf282.
- 125. **Zhang** et al., What's the relative risk? A method of correcting the odds ratio in cohort studies of common outcomes, JAMA, 80:19, 1690, doi:10.1001/jama.280.19.1690.
- 126. **Altman**, D., How to obtain the P value from a confidence interval, BMJ, doi:10.1136/bmj.d2304.
- 127. **Altman (B)** et al., How to obtain the confidence interval from a P value, BMJ, doi:10.1136/bmj.d2090.
- 128. **Sweeting** et al., What to add to nothing? Use and avoidance of continuity corrections in meta-analysis of sparse data, Statistics in Medicine, doi:10.1002/sim.1761.
- 129. **Deng**, H., PyMeta, Python module for meta-analysis, www.pymeta.com/.

