

# Coexistence theory for microbial ecology, and vice versa

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## Abstract

1

2 Classical models from theoretical ecology are seeing increasing uptake in microbial ecology, but there  
3 remains rich potential for closer cross-pollination. Here we explore opportunities for stronger integration of  
4 ecological theory into microbial research (and vice versa) through the lens of so-called “modern” coexistence  
5 theory. Coexistence theory encompasses a body of theory for disentangling the contributions of different  
6 fluctuation-independent (e.g., resource partitioning) and fluctuation-dependent (e.g., environmental  
7 variability) mechanisms to species coexistence. We begin with a short primer on the fundamental concepts  
8 of coexistence theory, with an emphasis on the relevance to microbial communities. We next present  
9 a systematic review, which highlights the paucity of empirical applications of coexistence theory in  
10 microbial systems. In light of this gap, we then identify and discuss ways in which: i) coexistence  
11 theory can help to answer fundamental and applied questions in microbial ecology, particularly in  
12 spatio-temporally heterogenous environments, and ii) experimental microbial systems can be leveraged  
13 to validate and advance coexistence theory. Finally, we address several unique, but often surmountable,  
14 empirical challenges posed by microbial systems, as well as some conceptual limitations. Nevertheless,  
15 thoughtful integration of coexistence theory into microbial ecology presents a wealth of opportunities for  
16 the advancement of both theoretical and microbial ecology.

## 17 Introduction

18 Sustained improvement in sequencing technologies, database integration, and bioinformatics are accelerat-  
19 ing the accumulation of microbial community census data. At the same time there is growing awareness  
20 that these empirical developments have outpaced advancements in our mechanistic understanding of  
21 microbial community dynamics (Prosser, 2020). To address this imbalance, there has been a recent push  
22 to integrate models and frameworks from theoretical ecology into microbial ecology (Picot, Shibasaki,  
23 Meacock, & Mitri, 2023; van den Berg et al., 2022; Prosser et al., 2007; Meroz, Livny, & Friedman, 2024),  
24 with theory-driven research already providing deep insights into the assembly (Goldford et al., 2018;  
25 Friedman, Higgins, & Gore, 2017), functioning (Skwara et al., 2023), and stability (Hu, Amor, Barbier,  
26 Bunin, & Gore, 2022) of microbial communities.

27 Understanding species coexistence and competition has been a central goal of theoretical ecology for over  
28 a century (Gause, 1935; MacArthur & Levins, 1967; Tilman, 1982; Chesson, 2000b). With growing insight  
29 into the essential role microbes play in regulating organismal and ecosystem health, understanding the  
30 causes and consequences of species coexistence has become increasingly relevant to applied and fundamental  
31 microbiology. For instance, the maximization of ecosystem functioning (e.g., starch degradation) in  
32 bacterial communities can require the coexistence of specific combinations of species (Sanchez-Gorostiaga,  
33 Bajić, Osborne, Poyatos, & Sanchez, 2019), and the evolution of antimicrobial resistance can be shaped by  
34 how different environmental conditions influence the coexistence of susceptible and resistant strains (Nev,  
35 Jepson, Beardmore, & Gudelj, 2020; Letten, Hall, & Levine, 2021). A number of different overlapping  
36 frameworks have been developed in ecology for understanding species coexistence (Chase & Leibold,  
37 2003; Hubbell, 2011; Abrams, 2022; Clark et al., 2024), some of which (e.g., resource competition theory)  
38 are especially well suited to microbial systems (Grover, 1997). However, one approach that has become  
39 popular amongst plant and animal ecologists, but that has seen far less uptake in microbial ecology, is  
40 so-called ‘modern coexistence theory’ (Chesson, 2000b; Barabás, D’Andrea, & Stump, 2018).

41 The prefix *modern* (dropped in the remainder of the text) is something of a misnomer in the sense  
42 that many of the core ideas date back several decades (Chesson & Warner, 1981; Chesson, 1990, 1994;  
43 May, 1973) (albeit with continuous development to the present) and that it has not superseded other  
44 approaches (Abrams, 2022). Nevertheless, its rapid uptake in recent years can be understood, at least in  
45 part, as a reaction to the confusing morass of system- and scale-specific coexistence mechanisms that  
46 theoretical and empirical ecologists had offered up by the end of the 20<sup>th</sup> century. It was against this  
47 backdrop that John Lawton famously described community ecology as “a mess, with so much contingency  
48 that useful generalisations are hard to find” (Lawton, 1999). Coexistence theory, developed primarily  
49 by Peter Chesson and colleagues (hence also referred to as ‘Chesson’s coexistence theory’) emerged as a  
50 unifying framework that brought a welcome degree of order to the study of species coexistence (Chesson,  
51 1994, 2000b; Barabás et al., 2018; Adler, HilleRisLambers, & Levine, 2007). More specifically, coexistence  
52 theory provides a quantitative framework for sorting the many low-level (e.g. system-specific) coexistence  
53 mechanisms into a small number of high-level umbrella categories. As such, it concentrates and links many  
54 disparate processes, by showing how, for example, temporal fluctuations in temperature, nectar chemistry  
55 and rainfall, can mediate coexistence in aquatic plants, floral yeasts, and annual grasses, respectively, via  
56 the same underlying mechanism (Armitage & Jones, 2019b; Letten, Dhami, Ke, & Fukami, 2018; Angert,  
57 Huxman, Chesson, & Venable, 2009).

58 The purpose of this review is to highlight the wealth of opportunities for applications of coexistence theory  
59 in microbial ecology, and the equally rich potential for testing coexistence theory with microbial systems.  
60 We begin with “*A coexistence theory primer*”, which provides a brief summary of the fundamental concepts  
61 of coexistence theory, but point readers wishing to go deeper to existing reviews detailing the mathematical

62 intricacies of coexistence theory and guidelines for its empirical implementation (see Barabás et al., 2018;  
63 Godwin, Chang, & Cardinale, 2020; Spaak, Ke, Letten, & De Laender, 2023; Chesson, 2018; Ellner,  
64 Snyder, Adler, & Hooker, 2019; E. C. Johnson & Hastings, 2023). Next in “*Empirical applications*” we  
65 present the results of a systematic review of existing empirical studies employing coexistence theory in  
66 microbial systems. Then in “*Mutual benefits of coexistence theory and microbial ecology*” we discuss how  
67 coexistence theory is well suited to tackling a range of fundamental and applied problems in microbial  
68 ecology, and conversely how the tractability of microbial systems makes them ideal for testing and  
69 developing emerging branches of coexistence theory. Finally, in “*Cautionary notes*” we identify some of  
70 the empirical challenges and fundamental limitations of coexistence theory, especially in the context of  
71 microbial study systems. Indiscriminately applying coexistence theory as an additional “off-the-shelf”  
72 analysis risks losing sight of the ecological questions and processes of interest. Nevertheless, thoughtful  
73 integration of coexistence theory and microbial ecology holds great promise for generating new insights in  
74 both fields.

## 75 **A coexistence theory primer**

76 The framework of coexistence theory is best understood as two related approaches for expressing  
77 competitors’ invasion growth rates as a small combination of mechanisms fundamental to coexistence.  
78 Here, invasion growth rates are a species’ (or genotype’s) long term average growth rate when introduced  
79 at very low density into an established (resident) community of potential competitor species at equilibrium  
80 or within a dynamic attractor. If invasion growth rates are positive for all species within a community,  
81 then they are said to be able to coexist. The critical information recovered from these invasion growth  
82 rates are generally either: 1) competitors’ niche differences and fitness differences; or 2) competitors’  
83 responses to average environments and fluctuations around this average.

84 The first thread provides a higher-level framing of the requirements for coexistence along two fundamental  
85 axes. Specifically, stable coexistence among species depends on niche differences exceeding any inherent  
86 fitness differences (Chesson, 2000a, 2013; Letten, Ke, & Fukami, 2017; Spaak & De Laender, 2020). Niche  
87 differences capture the extent to which competitors use different resources (e.g. consumption of citrate  
88 versus glucose by different strains of *E. coli* in the long-term evolution experiment (Blount, Borland,  
89 & Lenski, 2008)) or are targeted by different predators or pathogens (e.g. specificity of bacteriophages  
90 to different bacterial strains or species (Koskella & Brockhurst, 2014)). In contrast, fitness differences  
91 reflect how well adapted competitors are to their shared environment. It follows that if two or more  
92 species are characterised by large fitness differences they can only coexist if their niches are sufficiently  
93 differentiated (Figure 1D). Conversely, when species have small fitness differences, even small niche  
94 differences can facilitate coexistence (note that a combination of infinitesimal fitness *and* niche differences  
95 can yield so-called neutral coexistence (Adler et al., 2007)). In the jargon of coexistence theory, a process  
96 that increases niche differences is referred to as a stabilizing mechanism while one that reduces fitness  
97 differences is referred to as an equalizing mechanism (Chesson, 2000a, 2003).

98 The second thread of coexistence theory is concerned with identifying the contributions of different  
99 stabilizing mechanisms to coexistence and partitioning them into additive terms reflecting various types  
100 of fluctuation-independent and fluctuation-dependent mechanisms (Chesson, 1994; Barabás et al., 2018;  
101 Ellner et al., 2019; Letten et al., 2018; E. C. Johnson & Hastings, 2023). Fluctuation-independent  
102 mechanisms promote coexistence in a constant environment, while fluctuation-dependent mechanisms act  
103 through environmental fluctuations to strengthen, weaken, or even reverse coexistence outcomes. The  
104 emphasis on stabilizing mechanisms reflects the prepotent role they play in mediating stable coexistence;  
105 stable coexistence is impossible in the absence of a stabilizing mechanism, and sufficient stabilization  
106 may depend on environmental fluctuations. Nevertheless, most mechanisms will also have an equalizing

107 component, as these two axes are not orthogonal. Under the standard partition, all fluctuation-independent  
108 mechanisms (including resource, predator and pathogen partitioning) are grouped into a single category.  
109 The fluctuation-dependent mechanisms capture the effects of both temporal *and* spatial heterogeneity  
110 on coexistence (hence they are also commonly referred to as variation-dependent mechanisms). The  
111 two main types of fluctuation-dependent mechanisms are the *storage effect* and *relative nonlinearity of*  
112 *competition*, both of which have temporal and spatial analogues (a third, exclusively spatial, mechanism  
113 is termed fitness-density covariance (Chesson, 2000a; Barabás et al., 2018)).

114 The temporal storage effect can facilitate coexistence when species exhibit different growth responses to  
115 density independent environmental factors (e.g., temperature or pharmaceutical antibiotics) that vary  
116 across space or fluctuate across time (Chesson, 1994; Letten et al., 2021). The emphasis on variation  
117 in density-independent environmental factors, which to a first approximation are not influenced by the  
118 focal species, is a distinguishing feature of the storage effect. In the jargon of coexistence theory, these  
119 species-specific responses can lead to density-dependence in environment-competition covariance (Chesson,  
120 1994; Yuan & Chesson, 2015; Barabás et al., 2018). This is simply to say that when a species is rare in the  
121 system it will experience little covariance in the strength of competition and environmental favourability  
122 across space or time, which allows it to take full advantage of good conditions. Conversely when a species  
123 is dominant in the system it will experience high positive covariance between these two factors, which  
124 should limit its ability to take advantage of favourable conditions. Provided rare species are also able to  
125 buffer the negative effects of high competition during unfavourable periods (e.g. via dormant life stages or  
126 overlapping generations), this process can drive the requisite negative frequency dependence underpinning  
127 species coexistence.

128 In contrast with the storage effect, relative nonlinearity relies on species exhibiting trade-offs in their  
129 per capita growth responses to competitive factors (cf. density-independent environmental factors), such  
130 as nutrient resources, which fluctuate through time (note that although there is a spatial analogue of  
131 relative nonlinearity, we focus on the more canonical temporal mechanism here) (Chesson, 1994; Yuan  
132 & Chesson, 2015; Barabás et al., 2018). These fluctuations may be driven endogenously (e.g., cyclic  
133 predator-prey dynamics) or via exogenous resource pulsing (e.g., in the animal gut). The classic trade-off  
134 permitting coexistence via relative nonlinearity is between gleaner and opportunists, which tend to be  
135 better competitors in continuous versus fluctuating resource environments (the name relative nonlinearity  
136 refers to the required difference in the nonlinearity of the per capita growth responses that permit this  
137 trade-off) (Yamamichi & Letten, 2022). Alongside the trade-off, stable coexistence via relative nonlinearity  
138 additionally requires that each species feedback on the magnitude of fluctuations in a direction that  
139 favours its competitor (Chesson, 1994; Yuan & Chesson, 2015; Barabás et al., 2018). For example,  
140 for coexistence of gleaners and opportunists, the former needs to increase temporal resource variability  
141 relative to that imposed by the opportunist. These negative feedbacks typically emerge as a natural  
142 byproduct of each strategist’s per-capita growth response, but it is also possible for positive feedbacks,  
143 and hence priority effects, to occur when competitors change the temporal pattern of resource availability  
144 in a direction which favours their own competitive ability (Ke & Letten, 2018).

145 These methods for partitioning invader-resident growth differences into an additive sum of contributing  
146 mechanisms have also been generalised into a method for assessing the role of any interspecific difference on  
147 coexistence. This has been called “trait-decomposition” in recent literature and quantifies the sensitivity  
148 of invasion growth rates to interspecific differences in model parameters such as nutrient uptake rates or  
149 mortality rates, all else being equal (Ellner et al., 2019).

## 150 Empirical applications

151 A variety of experimental and observational approaches have been used by researchers to confront the  
152 predictions and inference of coexistence theory with empirical data. Typically this involves the direct  
153 measurement of invasion growth rates via mutual invasion tests (Figure 1B), or the parameterization of  
154 dynamical models (e.g., Lotka-Volterra or consumer-resource models) using timeseries datasets (Figure  
155 1C) or “response surface” experiments that manipulate species’ densities (Figure 1A) (Grainger, Levine,  
156 & Gilbert, 2019; Terry & Armitage, 2024). The obtained estimates of invasion growth rates or model  
157 parameters may then be used to predict (or explain) coexistence based either on the partitioning of fitness  
158 and niche differences in equilibrium system (Figure 1D) or on the partitioning of different fluctuation-  
159 dependent and -independent mechanisms (Figure 1E) (Godwin et al., 2020; Ellner et al., 2019). Most  
160 empirical research employing coexistence theory has been conducted in plant systems with few studies in  
161 microbial systems; of the 49 studies that quantified niche and fitness differences reviewed by Terry &  
162 Armitage (2024), 39 focused on plant communities and just six studied microbial communities.

163 To confirm the rarity of empirical explorations of coexistence theory in microbial systems we performed a  
164 systematic review (see Supplementary Materials) that identified studies in two ways. First, we screened  
165 174 empirical coexistence studies compiled in previous systematic reviews of the field (Buche, Spaak,  
166 Jarillo, & De Laender, 2022; Terry & Armitage, 2024; Hawlena, Garrido, Cohen, Halle, & Cohen, 2022)  
167 and found nine studies that applied coexistence theory to microbial systems. Second, we performed an  
168 additional search of the literature in May 2024 and used a machine learning framework to screen abstracts  
169 (Van De Schoot et al., 2021). From an initial search that returned 2,164 records we found just 12 relevant  
170 studies (Table 1), including all nine relevant studies that had been identified from previous reviews.

171 This low number of studies precludes a formal analysis, but it does demonstrate how rarely coexistence  
172 theory has been applied in microbial systems. The 12 studies were published between 2013 and 2022  
173 (with no obvious increase over time) and they used bacteria ( $n = 5$ ), phytoplankton ( $n = 3$ ), protists ( $n =$   
174  $2$ ), or yeasts ( $n = 2$ ). Most studies (9/12) used mutual invasion tests (Figure 1B) and species sensitivity  
175 to competition (sensu Carroll, Cardinale, & Nisbet, 2011) to calculate niche and fitness differences. Two  
176 studies tracked the density of monocultures and multi-species communities over time (Figure 1C) and  
177 fitted population models to the timeseries data to either quantify niche and fitness differences (Hogle,  
178 Hepolehto, Ruokolainen, Cairns, & Hiltunen, 2022) or to quantify the relative contributions of different  
179 coexistence mechanisms (Letten et al., 2018). No studies used the response surface approach (Figure 1A)  
180 which dominates plant and animal empirical coexistence study designs (Terry & Armitage, 2024), and  
181 one study observed natural communities and used “performance proxies” (sensu Grainger, Levine, &  
182 Gilbert, 2019 for niche and fitness differences (Zufiaurre et al., 2021).

183 Some studies focused on the coexistence of just one pair of species (e.g., Tan, Rattray, Yang, & Jiang,  
184 2017; Hogle et al., 2022), while other studies investigated the coexistence of over 20 pairs of species  
185 (e.g., Li, Tan, Yang, Ma, & Jiang, 2019; Narwani, Alexandrou, Oakley, Carroll, & Cardinale, 2013). The  
186 tractability of these microbial systems result in the numbers of independent replicates far exceeding  
187 typical animal or plant experiments, with some studies having more than 500 experimental units (e.g., Li  
188 et al., 2019; Grainger, Letten, Gilbert, & Fukami, 2019). This increase in experimental units was not used  
189 to increase the replicates per treatment to gain more robust predictions (across the 12 relevant studies the  
190 maximum number of replicates was eight and the median was three). Instead, the additional experimental  
191 units were used to increase the number of species pairs examined (e.g., Li et al., 2019; Narwani et al.,  
192 2013) or to test the effects of additional factors such as the effect of environmental variables (e.g., Letten  
193 et al., 2018; Grainger, Letten, et al., 2019), trait diversity (eg., Hogle et al., 2022), or evolutionary history  
194 (e.g., Zhao, Zhang, & Zhang, 2016; Tan, Rattray, et al., 2017).

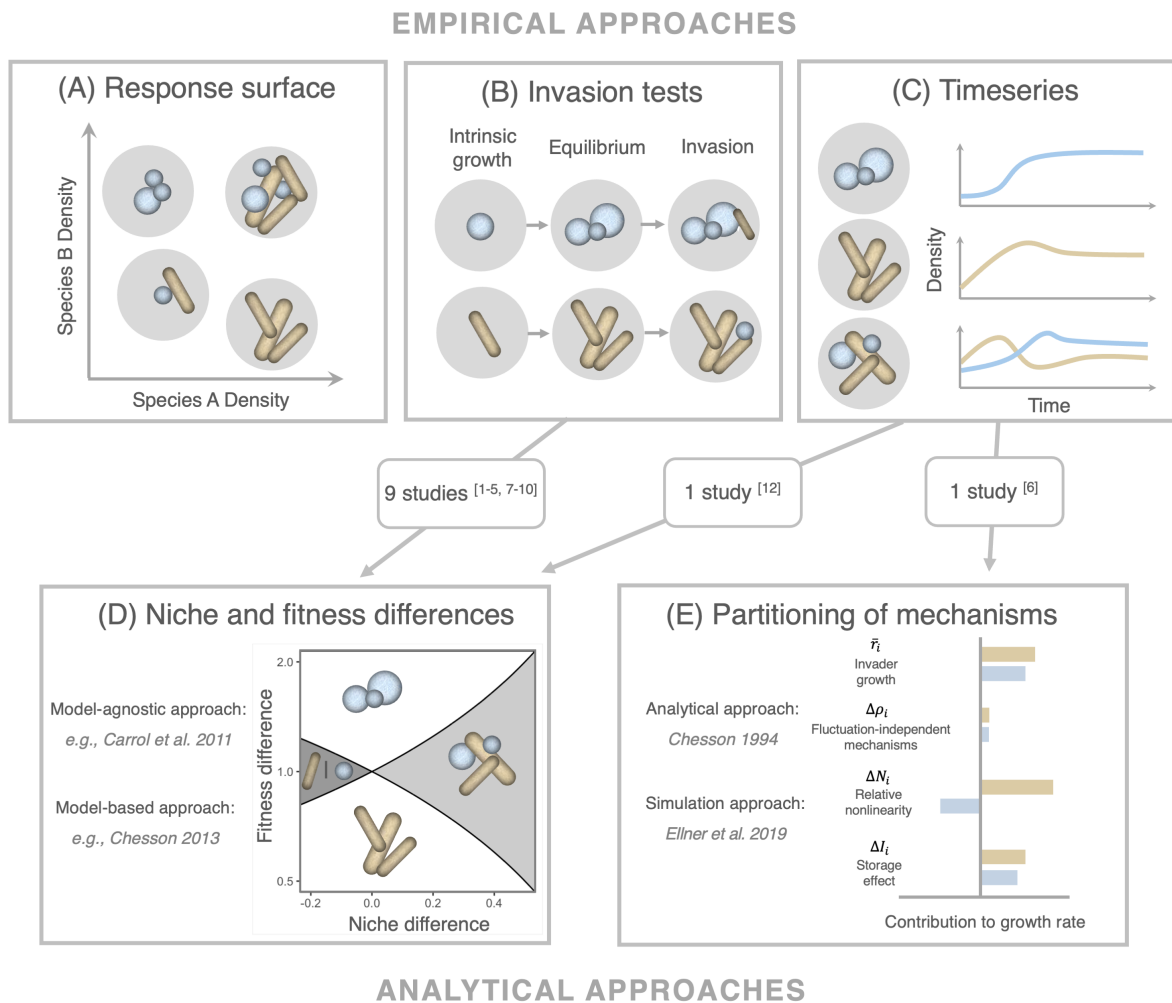


Figure 1: Approaches to data acquisition (A-C) and analysis (D-E) taken in empirical applications of coexistence theory. The arrows between panels show the number of studies in our systematic review that used that combination of empirical and analytical approaches. The numbers in superscripts refer to row numbers of Table 1. **(A)** Response surface designs, which can not always be applied in microbial systems (see *emph*Empirical challenges), are used to parameterize population models. **(B)** Invasion tests can be performed to test the mutual invasion criterion (i.e., coexistence predicted if all species can invade the community from low densities). **(C)** Timeseries datasets can be used to parameterize population models or to test coexistence theory predictions. **(D)** The most common analytical approach for applying coexistence theory is quantifying niche and fitness differences, either directly from the data through model-agnostic approaches or from parameterized population models using mathematical approaches. Communities can then be placed in a “coexistence plane” with axes defined by niche and fitness differences where different regions indicate either competitive exclusion (pale grey zones on top and bottom), stable coexistence (mid grey zone on the right), or priority effects (dark grey zone on the left). **(E)** Coexistence theory can also be used to partition the effects of different coexistence mechanisms either using analytical techniques or using simulation-based approaches. In this hypothetical example, there is stable coexistence between the blue and yellow species (both have positive invasion growth rates) primarily due to large contributions from fluctuation-dependent mechanisms.

Table 1: The twelve empirical coexistence studies using microbial systems identified by our systematic review. *Empirical Approach* describes what type of experimental design was used; mutual invasion tests (“invasion”), densities tracked over time (“timeseries”), or empirical studies where natural communities are observed and proxies are used to estimate niche and fitness differences (“proxies”). For *Analytical Approach*, “ND-FD” indicates studies that quantified niche and fitness differences and “partitioning” indicates studies that quantified the relative contributions of different coexistence mechanisms to invasion growth rates. *Model* indicates the population model used, *Pairs* records the number of species pairs for which coexistence was estimated, *Replicates* records the number of replicates per species pair (for each treatment), and *Units* records the number of distinct experimental units used in the coexistence part of the study.

Study	Taxa	Empirical Approach	Analytical Approach	Model	Pairs	Replicates	Units
Narwani et al., 2013	algae	invasion	ND-FD	none	28	3	168
Tan et al., 2016	bacteria	invasion	ND-FD	none	6	3	57
Zhao et al., 2016	bacteria	invasion	ND-FD	none	5	3	180
Tan, Rat-tray, et al., 2017	bacteria	invasion	ND-FD	none	1	5	60
Tan, Yang, & Jiang, 2017	bacteria	invasion	ND-FD	none	6	6	78
Letten et al., 2018	yeast	timeseries	partitioning	consumer-resource	6	4	160
Gallego et al., 2019	cyanobacteria	invasion	ND-FD	none	15	3	126
Grainger, Letten, et al., 2019	yeast	invasion	ND-FD	none	6	8	576
Li et al., 2019	bacteria	invasion	ND-FD	none	24	3	540
Jackrel et al., 2020	algae	invasion	ND-FD	none	6	3	72
Zufiaurre et al., 2021	protists	proxy	ND-FD	none	n/a	2	22
Hogle et al., 2022	protists	timeseries	ND-FD	lotka-volterra	1	4	24

## 195 **Mutual benefits of coexistence theory and microbial ecology**

196 To facilitate closer integration of coexistence theory and microbial ecology, in this section we explore  
197 the mutual benefits between the two areas of research. We first highlight how coexistence theory can  
198 provide a fresh perspective on key challenges in the study of microbial communities. We then argue  
199 that microbial communities provide unique opportunities for novel tests of coexistence theory that would  
200 otherwise be intractable (i.e., in macro-organisms).

### 201 **How coexistence theory can benefit microbial ecology**

202 Many mechanisms, some general to all ecological systems (e.g., resource and natural enemy partitioning)  
203 and others more common to microbial systems (e.g., cross-feeding, horizontal gene transfer), have been  
204 proposed to explain the high levels of microbial diversity commonly encountered in metabarcoding studies  
205 (Thompson et al., 2017). Coexistence theory can help microbial ecologists move beyond verbal theories  
206 and intuitions for how species coexist by quantifying the relative importance of these mechanisms and  
207 by relating different mechanisms to each other. Coexistence theory might be leveraged to synthesize  
208 disparate models in microbial ecology, and it holds particular promise for guiding the growing interest in  
209 how spatio-temporal variability impacts microbial communities. The remainder of this section will use  
210 three high-level examples to outline how different aspects of coexistence theory described in the primer  
211 section – (i) niche and fitness differences, (ii) fluctuation-dependent mechanisms of coexistence, and (iii)  
212 trait-decomposition simulations – can shine light on open problems in fundamental and applied microbial  
213 ecology.

214 A common approach taken by microbial ecologists (albeit one that is not unique to microbial ecology) is  
215 to infer species interactions and community assembly processes from the observed covariances between  
216 taxa in metagenomic/metabarcoding inventories (Armitage & Jones, 2019a). This includes characterizing  
217 communities as being under stochastic versus deterministic regulation, depending on the functional (or  
218 phylogenetic) distribution of co-occurring taxa (Stegen, Lin, Konopka, & Fredrickson, 2012). Although  
219 this data undoubtedly provides a valuable starting point for more mechanistic predictions, inference of  
220 assembly processes from observational data is well known to be fraught (Barner, Coblenz, Hacker, &  
221 Menge, 2018), not least because of the confounding effects of spatial and temporal scale dependence  
222 (Blanchet, Cazelles, & Gravel, 2020; Armitage & Jones, 2019a). Viewed from the perspective of niche and  
223 fitness differences it is apparent that all systems must fall along a continuum from stochastic (weak niche  
224 *and* fitness differences) to deterministic (strong fitness differences *or* strong niche differences), and that the  
225 magnitude of niche and fitness differences is going to be highly dependent upon the spatial and temporal  
226 scale at which they are evaluated. However, it is likewise unclear how the traditionally pairwise niche and  
227 fitness difference metrics relate to observed covariation among species in complex multispecies communities.  
228 Thus, we envision at least one way in which these approaches can complement one another. By tracking  
229 experimental or observational low density growth rates derived through metagenomic, metabarcoding, or  
230 plate count timeseries, we can begin to relate stabilising niche differences (a key requirement of invasion  
231 growth rates) to the topological properties of a community’s statistical correlational structure or its  
232 position along a predicted niche-neutral continuum. By benchmarking the inferential accuracy of these  
233 methods in experimental microbial communities in which each species’ invasion abilities are already  
234 known, we can identify the inferential ability of such approaches and their specific failure modes.

235 Understanding the impact of environmental fluctuations on eco-evolutionary dynamics is another in-  
236 creasingly active area of inquiry in microbial ecology (e.g. Abreu, Andersen Woltz, Friedman, & Gore,  
237 2020; Nguyen, Lara-Gutiérrez, & Stocker, 2021; Shibasaki, Mabilia, & Mitri, 2021). Microbial systems  
238 are rarely homogeneous, particularly at the temporal and spatial scales relevant in applied microbiology  
239 (Nguyen et al., 2021). This spatio-temporal variability – from periodic antibiotic dosing, to drying



240 and wetting of soils, to daily and seasonal fluctuations in temperature and light – undoubtedly plays  
241 a critical role in the eco-evolutionary dynamics of microbial systems. As opposed to most commonly  
242 applied ecological theory that assumes homogeneous environments (Meroz et al., 2024; Picot et al.,  
243 2023), coexistence theory offers a mathematically rigorous framework to systematically study the role of  
244 fluctuating environments and to partition the relative effects of different variation-dependent mechanisms  
245 on microbial coexistence. Furthermore, the stabilizing effects of spatio-temporal fluctuations may be  
246 leveraged to help engineer microbial communities for the optimization of ecosystem function (Letten &  
247 Ludington, 2023). Functional landscape approaches can be used to predict which combinations of species  
248 have the maximum performance for a given function across different applications from food and beverage  
249 production to waste management (Sanchez-Gorostiaga et al., 2019; Sanchez et al., 2023). However, these  
250 optimal communities may not have sufficient niche differences to overcome any fitness differences under  
251 standard conditions, so their coexistence might require the introduction of temporal or spatial fluctuations,  
252 which could be designed based on coexistence theory predictions. If, on the other hand, fluctuations are  
253 an unavoidable feature of the process, they will need to be considered in the design of microbial consortia.  
254 Using coexistence theory to better understand fluctuating environments therefore has the potential to  
255 advance both basic and applied microbial ecology.

256 As is common in many nascent fields, microbial ecology has seen a wide proliferation of alternative  
257 hypotheses and theories, with limited conceptual integration between them to date. Consider two popular  
258 theories concerning microbial coexistence: the seed bank and kill-the-winner models (Thingstad & Lignell,  
259 1997; Winter, Bouvier, Weinbauer, & Thingstad, 2010; Lennon & Jones, 2011; Lennon, den Hollander,  
260 Wilke-Berenguer, & Blath, 2021). The seed bank model posits that persistent populations of dormant or  
261 sporulated microbial cells can respond rapidly to transiently favourable environmental conditions and  
262 buffer their populations against losses they would incur if otherwise active and competing for resources  
263 (Lennon & Jones, 2011; Lennon et al., 2021). Although it has been loosely linked with the temporal  
264 storage effect in the past, recent work shows that microbial dormancy may also mediate coexistence  
265 via relative nonlinearity of competition when dormancy is adaptive under under periods of resource  
266 starvation (cf. density-independent stressors such as temperature, osmotic stress or antimicrobials)  
267 (Letten, Yamamichi, Richardson, & Ke, 2024). The “kill-the-winner” model, on the other hand, is a  
268 proposed fluctuation-independent mechanism by which lytic bacteriophage viruses – each specific to a  
269 single strain of bacterial competitor – act to suppress the abundance of otherwise competitively dominant  
270 bacteria (e.g. by virtue of being better resource competitors) (Thingstad & Lignell, 1997). It is reasonable  
271 to assume that trade-offs between growth and dormancy, and growth and phage resistance, frequently  
272 occur side-by-side, but we are aware of no efforts to theoretically synthesise them and assess their joint  
273 contributions to microbial coexistence. By unifying existing models of kill-the-winner and seed bank  
274 dynamics into a single community dynamics model, growth rate partitioning approaches could be used to  
275 evaluate their relative contribution to community average stabilization and fitness equalization (Ellner  
276 et al., 2019). This “trait-decomposition” approach (recently developed by Ellner et. al (2019)) would  
277 not only provide high-level inference on the importance of these two prominent microbial coexistence  
278 mechanisms, but would also allow for the further partitioning of the fluctuation-independent (e.g. classic  
279 resource competition vs. trade-offs in phage susceptibility) and fluctuation-dependent contributions (i.e.  
280 temporal storage effect vs relative nonlinearity).

## 281 **How microbial ecology can benefit coexistence theory**

282 The development of coexistence theory has undoubtedly outpaced its empirical validation (Godwin et al.,  
283 2020; Terry & Armitage, 2024). This lag is at least in part due to the comparatively technical nature  
284 of early presentations of the theory, but it is also due to the challenges of testing the theory in plant  
285 and animal systems. Most empirical coexistence studies of animal and plant communities are conducted

286 over a single generation due to logistical constraints (Terry & Armitage, 2024, but see Terry, 2024),  
287 which means coexistence theory can only be used to produce (error-prone) predictions rather than to  
288 explain observations. However, the short generation times and rapid dynamics of microbes allow for  
289 direct observations of coexistence, competitive exclusion, or priority effects (i.e., through invasion tests or  
290 timeseries). As such, with microbes, it is much easier to both make and test predictions informed by  
291 coexistence theory. This tight connection between theory and experiments places microbial systems in an  
292 excellent position to rigorously test and to develop emerging theory on a range of themes in coexistence  
293 theory, including, but not limited to, spatiotemporal fluctuations as coexistence mechanisms, evolutionary  
294 effects on coexistence, and coexistence in diverse multispecies communities.

295 The challenges of manipulating environmental variability at meaningful temporal and spatial scales  
296 in animal and plant systems has hindered empirical research on fluctuation-dependent mechanisms of  
297 coexistence – e.g., the storage effect and relative non-linearity of competition. Firstly, as environmental  
298 fluctuations must occur on timescales longer than generation times to act as stabilizing mechanisms,  
299 studies of temporal storage effects and related mechanisms in plant and animal systems have typically  
300 relied on simulation approaches with parameterized models (e.g., Armitage & Jones, 2019b; Hallett,  
301 Shoemaker, White, & Suding, 2019). In contrast, empirical tests of fluctuation-dependent coexistence  
302 mechanisms, that require multi-year experiments for annual plants, can be done in days for bacteria. It is  
303 unsurprising then that the few direct empirical tests (cf. simulation-based predictions) of fluctuation-  
304 dependent coexistence have mostly been carried out in microbial systems (e.g., Descamps-Julien &  
305 Gonzalez, 2005; Jiang & Morin, 2007; Ellner, Snyder, & Adler, 2016; Letten et al., 2018). Secondly,  
306 removing or manipulating spatial heterogeneity in plant and animal experimental systems is often not  
307 feasible. Experimental arenas for microbial communities, on the other hand, can be easily modified to  
308 create or remove spatio-temporal variability in environmental conditions (e.g., using a chemostat). One of  
309 the few studies that has empirically quantified spatial coexistence mechanisms used found higher diversity  
310 of *Pseudomonas* strains in static (heterogeneous) compared to shaken (homogeneous) environments when  
311 dispersal between environments was permitted (Tan, Rattray, et al., 2017). Modified chemostats with  
312 gradients of environmental conditions (i.e., “gradostats”, *sensu* Lovitt & Wimpenny, 1981), complex  
313 artificial “micro-landscapes” (Larsen & Hargreaves, 2020), or biofilm model systems (O’Brien & Fothergill,  
314 2017) all offer more sophisticated and highly controllable approaches for testing the effects of spatial  
315 heterogeneity on species coexistence.

316 Amidst growing interest in the role of rapid evolution in regulating community dynamics and coexistence  
317 on ecological time scales (Lankau, 2011; Hiltunen, Kaitala, Laakso, & Becks, 2017; Wittmann & Fukami,  
318 2018; Yamamichi & Letten, 2021), several recent studies have shown that evolution can shift niche or  
319 fitness differences through changes in species traits and competitive abilities. However, with only a  
320 few exceptions (e.g., Bernhardt et al., 2020) these are limited to studying sorting of standing genetic  
321 variation rather than *de novo* evolution (Sakarchi & Germain, 2023; Hart, Turcotte, & Levine, 2019).  
322 The rapid generation times and large population sizes of microbes permit observation of evolutionary  
323 impacts on species coexistence over relatively short timescales. In two rare examples, Zhao et al., (2016)  
324 studied coexistence between allopatrically and sympatrically evolved pairs of bacteria, while Hogle et  
325 al., (2022) observed community dynamics and species coexistence over 70 generations of ciliates (a study  
326 that would have taken an annual plant ecologist 70 years). Furthermore, precise genetic manipulation of  
327 microbial populations (e.g., transfer of antimicrobial resistant genes) could deepen our understanding of  
328 the molecular basis of traits that shape species coexistence. Expanding coexistence studies into microbial  
329 systems also has the potential to refine our understanding of the processes responsible for the persistence  
330 or loss of allelic diversity in evolving populations, as the framework’s ideas naturally map to population  
331 genetic processes such as clonal interference and negative frequency-dependent selection (Maddamsetti,  
332 Lenski, & Barrick, 2015; Letten et al., 2021).

333 The small-scale nature of microbial systems also allows the use of far more experimental units than  
334 realistically achievable in animal and plant study systems. This is to say that the “combinatorial explosion  
335 problem”, where the number of species combinations increases exponentially with species richness, is  
336 far less of a limiting factor in microbial systems. Indeed, Li et al., (2019) used over 500 experimental  
337 units to quantify niche and fitness difference between 24 pairs of bacterial species. High-throughput  
338 robotic or droplet-based systems, which can rapidly assemble and observe the dynamics of many different  
339 microbial communities (e.g., Diaz-Colunga, Catalan, San Roman, Arrabal, & Sanchez, 2024; Kehe et al.,  
340 2019), would be especially powerful tools for testing emerging theory on species coexistence in diverse  
341 communities where indirect interactions can significantly complicate predictions of species coexistence  
342 (Spaak & Schreiber, 2023).

## 343 **Cautionary notes**

344 There are inherent features of microbial systems that introduce novel challenges for applying coexistence  
345 theory. Moreover, this framework is not a silver bullet for investigating all problems related to species  
346 coexistence. As such, awareness of the constraints and limitations in implementing coexistence theory is  
347 essential for its effective use in microbial ecology.

## 348 **Empirical challenges**

349 While the fast growth and short generations of microbes are a convenience in many circumstances (see  
350 above), they can also present unique challenges for empirical application of coexistence theory. For  
351 response surface experiments, where species’ densities must be finely controlled (Inouye, 2001), the  
352 fast dynamics of microbial systems are potentially prohibitive. It is therefore unsurprising that our  
353 systematic review found no studies applying this approach. For mutual invasion tests, where a key  
354 assumption is that the resident community is at equilibrium when the invader is introduced, batch  
355 culture experiments are inappropriate as they do not allow for community dynamics to establish a stable  
356 equilibrium. High-frequency serial transfer, or better still, chemostat systems, should instead be used to  
357 ensure that resident communities are indeed at equilibrium (Picot et al., 2023), so that invader growth  
358 rates can be accurately estimated. For timeseries approaches in microbial systems, it may be important  
359 to consider eco-evolutionary dynamics when fitting population models to estimate species interaction  
360 coefficients. Rapid evolution may cause species interactions to change over time and dramatic shifts  
361 in population structure of a given species can even occur between different growth stages (Zambrano,  
362 Siegle, Almirón, Tormo, & Kolter, 1993).

363 Microbial communities also generally exhibit much higher phylogenetic and biochemical diversity than  
364 animal and plant communities (Prosser et al., 2007). While understanding the coexistence of two  
365 macroorganisms (e.g., endangered wolves and common coyotes) is often critical for conservation and  
366 ecosystem management, it is less common for the coexistence of just two microbial taxa to have significant  
367 implications in applied settings (but see, for example, the balance of Bacteroidetes and Firmicutes in the  
368 mammalian gut). As such, the diversity of microbial communities may seem at odds with coexistence  
369 theory, which has traditionally used species pairs as the focal study unit. Indeed, the concepts of niche  
370 and fitness differences were originally formulated for two competitors from the same trophic level, and  
371 the limitations of invasion analysis when studying more than two species have long been acknowledged  
372 (MacArthur & Levins, 1967; Spaak & Schreiber, 2023). Extensions of coexistence theory to multi-trophic  
373 systems, or to systems with three or more competitors from the same trophic level, are therefore at the  
374 forefront of theoretical work on coexistence theory (Chesson, 2018; Spaak & Schreiber, 2023; Song &  
375 Spaak, 2024; Ranjan, Koffel, & Klausmeier, 2024), and are likely to be important for microbial applications  
376 of this framework.

377 High frequencies of non-competitive or context-dependent interactions (Kehe et al., 2021; Momeni,  
378 Xie, & Shou, 2017; Kost, Patil, Friedman, Garcia, & Ralser, 2023) are additional features of microbial  
379 communities that complicate the application of coexistence theory. Facilitation can be challenging to  
380 model with traditional tools (e.g., Lotka-Volterra) and most definitions of niche and fitness differences  
381 – including the most popular metrics such as Chesson’s classic square root equations (Chesson, 1990;  
382 Chesson & Kuang, 2008; Chesson, 2013) and the sensitivity to competition formula of Carroll et al.  
383 (2011) – do not account for positive interactions between species (Spaak & De Laender, 2020). However,  
384 such interactions are seemingly ubiquitous in microbial communities with ample evidence of cross-feeding  
385 (Dal Bello, Lee, Goyal, & Gore, 2021), multi-species biofilm formation (Nadell, Drescher, & Foster,  
386 2016), and sharing of antibiotic resistance genes (Ellabaan, Munck, Porse, Imamovic, & Sommer, 2021).  
387 Further, interspecific interactions among microbes have been shown to readily switch signs from facilitative  
388 to competitive depending on the local environmental context (Hoek et al., 2016; Meroz et al., 2024).  
389 Non-competitive interactions are not beyond the scope of coexistence theory – new metrics for niche and  
390 fitness differences that can accommodate positive interactions have recently been developed (Spaak &  
391 De Laender, 2020; Koffel, Daufresne, & Klausmeier, 2021) – but they are nonetheless difficult to integrate  
392 with traditional approaches. Indeed, the sign flexibility of interspecific interactions in microbes merits  
393 further study as it may be one pathway from which fluctuation-dependent mechanisms can emerge even  
394 in the absence of external environmental variation.

## 395 **Limitations and conceptual mismatches**

396 Several of the empirical challenges discussed above can be addressed – at least conceptually – through  
397 recent extensions to the original theory. However, there are some limitations of the theory that must be  
398 treated with caution. One of the most obvious limitations, which has received considerable attention in  
399 the ecological literature, is that invasion analysis does not always predict coexistence. The analytical  
400 approaches of applying coexistence theory (Figure 1D and E) are built upon the assumption that mutual  
401 invasibility predicts coexistence. However, it is easy to imagine cases where all species can invade but  
402 will not ultimately coexist or where not all species cannot invade even if they could all coexist (Barabás  
403 et al., 2018; E. Johnson & Hastings, 2022; Clark et al., 2024). Although complex ecological dynamics  
404 (e.g., Allee effects) and stochasticity (both environmental and demographic) can break the simple logic of  
405 invasion analysis, even in multispecies systems, invasion growth rates have been shown to be broadly  
406 informative (Chesson, 2018; Schreiber, Levine, Godoy, Kraft, & Hart, 2023; Clark et al., 2024).

407 Another shortcoming of coexistence theory is the (over)emphasis it has traditionally placed on qualitative  
408 (e.g. coexistence vs exclusion), rather than the quantitative, community states. Often, however, relative  
409 abundances of coexisting species are an equally, if not more, important response variable (Abrams, 2022).  
410 If multiple species coexist but one is far more abundant, the community may function like a monoculture.  
411 For instance, lakes dominated by toxic algal blooms often have communities where cyanobacteria, diatoms,  
412 and green algae are all coexisting, but where the cyanobacteria dominate by orders of magnitude (Scheffer,  
413 Rinaldi, Gagnani, Mur, & van Nes, 1997; Grover, 1997; Jankowiak, Hattenrath-Lehmann, Kramer,  
414 Ladds, & Gobler, 2019). Similarly, predicting if a pathogenic microbe can coexist with (or be excluded  
415 by) beneficial microbes may not be as useful as predicting the abundance of the pathogen (Letten et al.,  
416 2021). If the pathogen coexists with the other microbes but is held at low density (i.e., below the minimal  
417 infective dose), it may be of no material consequence for the host. Nevertheless, with the data required  
418 to evaluate qualitative community states informed by coexistence theory, it is usually always possible to  
419 quantify other response variables of interest (e.g relative abundance at equilibrium, invasion growth rates  
420 or time to extinction (Clark et al., 2024)) that may be especially relevant in more applied contexts.

421 Finally, common uses of coexistence theory – specifically the quantification of niche and fitness differences

422 – tells us *if* species coexist but not necessarily *how* they coexist. Niche and fitness differences summarize  
423 the combined effects of many underlying mechanisms, so focusing solely on these properties risks obscuring  
424 underlying ecological processes. This is particularly true if phenomenological models (e.g., Lotka-Volterra  
425 competition) rather than mechanistic models (e.g., resource-consumer models) are used to estimate niche  
426 and fitness differences, which has been the dominant approach of applying coexistence theory to date  
427 (Chesson, 2013; Godwin et al., 2020). Indeed, phenomenological approaches, such as the widely-used  
428 generalized Lotka-Volterra model, are far more common than mechanistic approaches in the microbial  
429 literature (Picot et al., 2023). The field of microbiology, however, has a rich history of precisely identifying  
430 and manipulating the biochemical processes underlying an organism’s ecology, resulting in the development  
431 of metabolic models capable of predicting microbial growth from first principles (Delattre, Desmond-  
432 Le Quéméner, Duquennoi, Filali, & Bouchez, 2019). Incorporating these more sophisticated models  
433 into the coexistence framework will be challenging but likely fruitful, expanding our ability to make  
434 mechanistically informed manipulations of diverse microbial systems in applied contexts.

## 435 **Conclusion**

436 With our systematic literature search finding limited uptake of coexistence theory in microbial ecology to  
437 date, we hope that the observations and opportunities outlined in this review can act as stimulus for closer  
438 cross-pollination between these two fields. This includes leveraging coexistence theory to foster rigour and  
439 conceptual synthesis to the study of coexistence and community assembly in microbial systems, as well as  
440 taking advantage of the high-throughput of microbial systems to push the frontier of coexistence theory  
441 forward. Echoing broader concerns in microbial ecology (Prosser, 2020), it is of course important that  
442 coexistence theory is not merely appended to descriptive studies to provide an illusion of theory-driven  
443 research. The ever-expanding framework of coexistence theory will only benefit microbial ecology if  
444 it is applied appropriately and is used to inform study design as well as data analysis. Nevertheless,  
445 thoughtfully incorporating coexistence theory into microbial ecology offers numerous opportunities to  
446 explore new research avenues, driving progress in theoretical and microbial ecology alike.

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## 449 Author Contributions

450 JAO, DWA, and ADL conceived the research. JAO performed the systematic review and wrote the first  
451 draft of the manuscript with input from ADL and DWA. All authors contributed to the final manuscript.

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# Supplementary Material for

## Coexistence theory for microbial ecology, and vice versa

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# 1 Overview of systematic review

We performed a systematic review to find empirical coexistence theory conducted in microbial systems. First we established three distinct inclusion criteria that a study had to meet in order to be included (Fig. S1). We considered a study relevant if it was primary empirical research and it was conducted in microbial systems and it applied (modern) coexistence theory. We identified relevant studies through previous systematic reviews and by performing our own search of the literature using a machine learning framework for abstract screening (Fig. S2).

The previous systematic reviews that we initially used to identify studies were of: (i) 29 empirical studies where both niche and fitness differences could be quantified (Buche, Spaak, Jarillo, & De Laender, 2022), (ii) 49 empirical studies that empirically applied any form of coexistence theory (Terry & Armitage, 2024), and (iii) 96 empirical studies that generally tested mechanisms of species coexistence (Hawlena, Garrido, Cohen, Halle, & Cohen, 2022). Of the 174 studies identified from previous reviews, 15 studies were potentially relevant based on how they had been labelled by the authors of those reviews (Fig. S2). Six of these studies were excluded at the full text screening stage for not meeting at least one of our inclusion criteria (Fig. S1). The remaining nine studies were included in our systematic review.

Guided by the search terms used by the previous systematic reviews, we then performed our own search of the literature and we used a novel machine learning framework for abstract screening. The methods and results of this AI-aided literature review are outlined below.

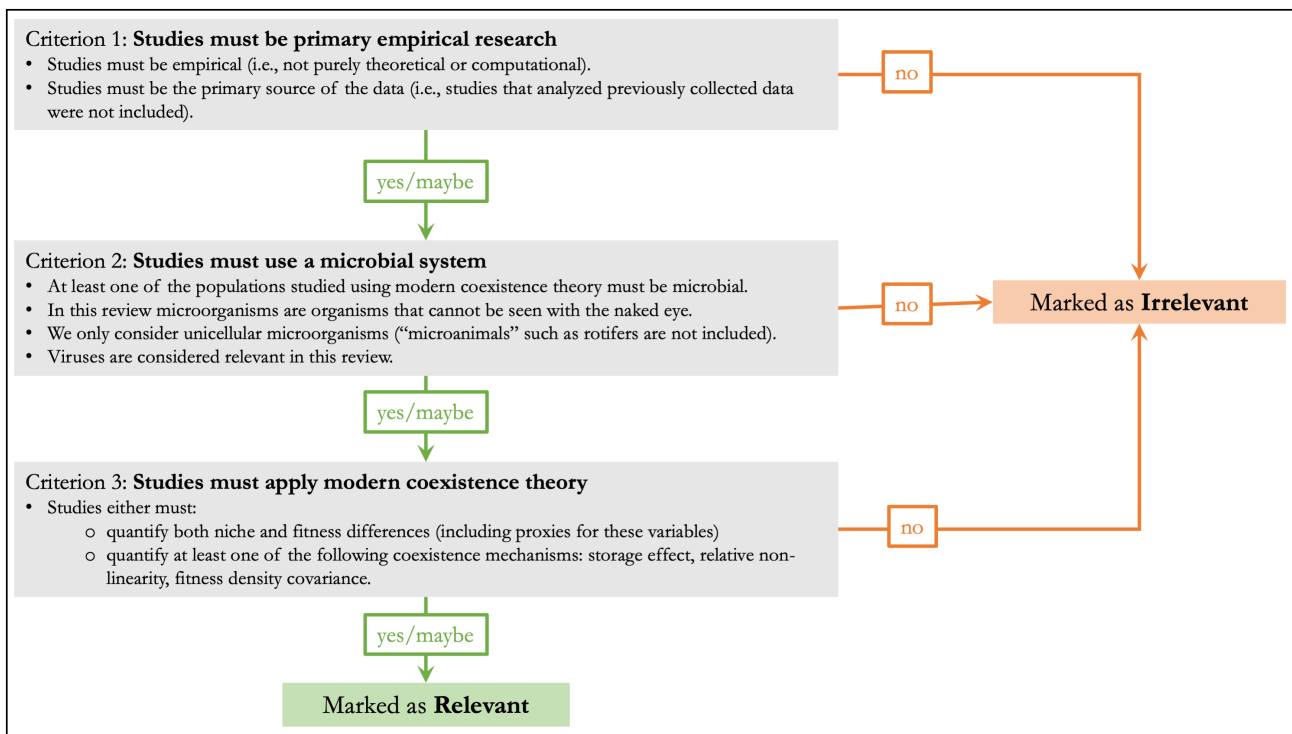


Figure S1: Decision tree with our three inclusion criteria. For a study to be included it had to meet all three criteria. This decision tree was also used during abstract screening where “yes” or “maybe” led to a record being marked as (potentially) relevant.

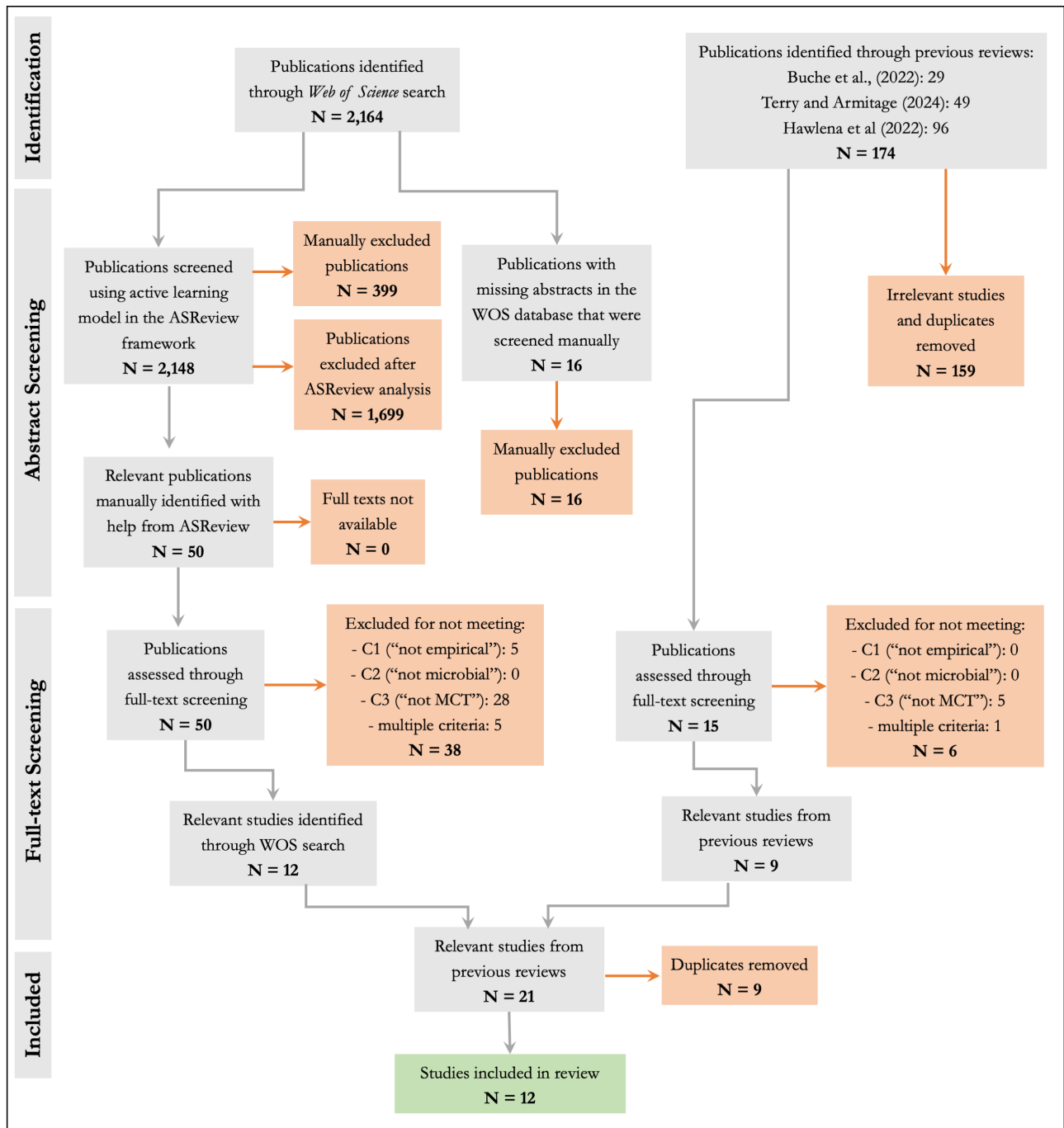


Figure S2: PRISMA-style flow chart summarizing the steps of our systematic review from study identification, to abstract screening to full-text screening, to study inclusion.

## 2 AI-aided literature review

A literature search was performed on *Web of Science* on the 19<sup>th</sup> of May 2024 using the following advanced search where a study needed to have a word associated with microbial systems *and* a word associated with modern coexistence theory in either its title, abstract, or keywords:

**Web of Science search.** TS = Topic (title, abstract, or keyword).

TS = (“microb\*” OR “microorganism\*” OR “bacteri\*” OR “fung\*” OR “yeast\*” OR “alga\*” OR “phytoplankton” OR “diatom\*” OR “cyanobacteria” OR “protozoa” OR “protist\*” OR “ciliate\*” OR “archaea” OR “virus\*” OR “biofilm”)

AND

TS = (“coexistence theory” OR “co-existence theory” OR “species coexistence” OR “species coexistence” OR “niche differ\*” OR “fitness diff\*” OR “niche overlap” OR “stabilising mechanism\*” OR “equalising mechanism\*” OR “fitness ratio\*” OR “fluctuation-\*dependent” OR “fluctuation \*dependent” OR “relative non-linearit\*” OR “relative non linearit\*” OR “storage effect\*” OR “lottery effect\*” OR “lottery model\*” OR “invas\* criteri\*” OR “invas\* condition\*”)

This broad search returned 2,164 records, including all nine relevant studies that had been identified from previous systematic reviews. We then used a machine learning framework called *ASReview*, where active learning models help to accelerate abstract screening (Van De Schoot et al., 2021). In summary, a human screener will input their unlabelled dataset to the model and they will identify some “training” data (labelled abstracts that are known to be relevant or irrelevant based on prior knowledge). The active learning model then ranks the entire unlabelled dataset in order of relevancy based on the words (or sentences) that are found in the abstracts that were marked by the human as irrelevant or relevant. The paper that the active learning model marks as most relevant is shown to the human screener, who then reads that abstract and uses their inclusion criteria to determine whether to mark it as relevant or irrelevant. The active learning model is then updated based on the decision of the human screener and the order of the remaining records in the unlabelled dataset are updated based on their new relevancy scores. This screening process continues until some *a priori* stopping criterion is met. If the active learning model is working as expected, plotting the number of records screened against the number of relevant records found should return a saturating curve.

This framework requires that all records have abstracts, but there were 16 papers in our search results that did not have abstracts. The full texts of these papers were screened and all 16 were marked as irrelevant. The remaining 2,148 papers were screened using *ASReview*. The importance of the training data for these active learning models has been shown to be extremely low, given that the models are constantly being updated. Nonetheless, for the relevant training records we chose three studies from the nine relevant studies identified through previous reviews that were diverse in terms of the study organisms and approach of applying coexistence theory (Letten, Dhimi, Ke, & Fukami, 2018; Li, Tan, Yang, Ma, & Jiang, 2019; Narwani, Alexandrou, Oakley, Carroll, & Cardinale, 2013), and for the irrelevant training records we randomly selected three records that were confirmed to be irrelevant. Our *a priori* stopping criterion, which was informed by a recent simulation study (Campos et al., 2024), was a combination of time driven and data driven heuristics where screening would stop when at least 20% of the records had been screened and then when the number of records marked as irrelevant in a row equalled at least 5% of the total number of records marked as irrelevant. We used the default active learning model settings (i.e., “Naive Bayes” as the classifier and “Term Frequency-Inverse Document

Frequency” for feature extraction). This combination works well for fields where terminology is well defined (e.g., “niche differentiation” or “temporal storage effect” have very specific meanings) and has been shown to be very efficient and accurate in simulation studies (Van De Schoot et al., 2021; Campos et al., 2024).

By the time our stopping criterion was met, we had marked 50 records as relevant and 399 records as irrelevant. When we stopped the abstract screening process, 65 records had been marked as irrelevant in a row. All nine relevant records from previous studies had been identified during the abstract screening process and the recall curve was clearly saturating (Fig. S3). 1,699 records were automatically excluded as they were not suggested to be relevant by the active learning model before the stopping criterion was met. The 50 records manually marked as relevant progressed to full text screening and all of their full texts were available. Following full-text screening, 38 of these records were excluded (five studies were not empirical, 28 studies did not use coexistence theory, and five studies did not meet multiple inclusion criteria). The 12 studies that passed through full-text screening included the nine relevant studies identified from previous reviews as well as three additional relevant studies (Fig. S2).

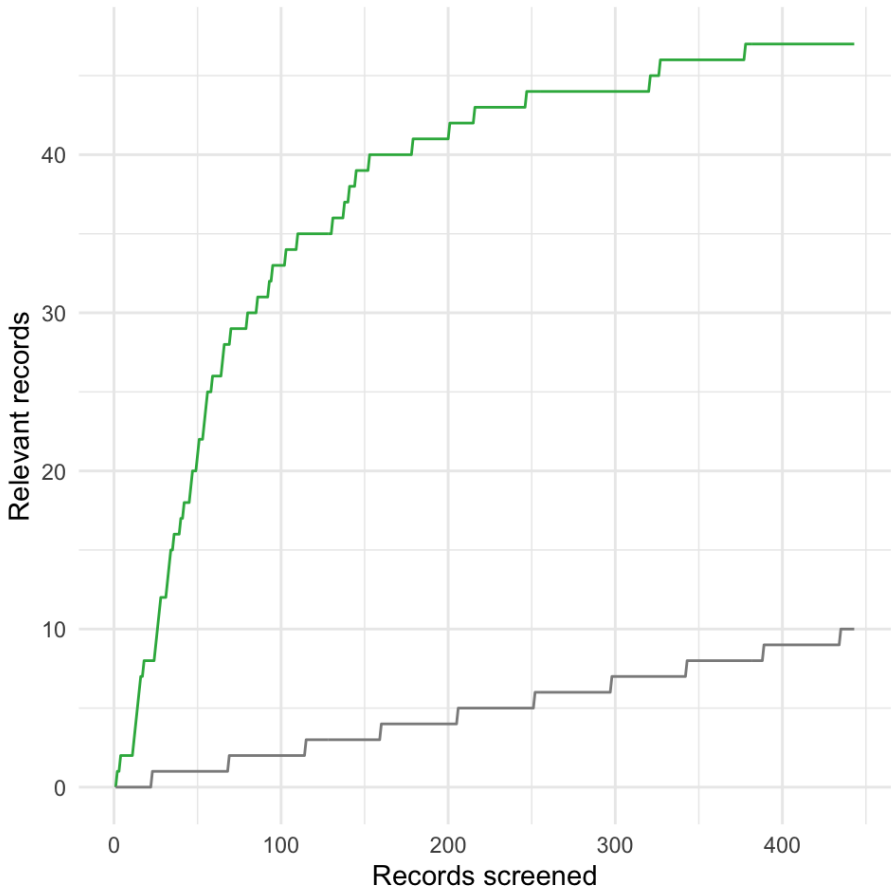


Figure S3: Recall curve showing the number of relevant records identified plotted against the number of records screened (green line). The grey line shows the number of relevant records that would have been expected by random sampling of the unlabelled dataset (i.e., traditional abstract screening). The gap between the green and the grey line shows the efficiency of the machine learning abstract screening framework.

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