

1 **Pharmacodynamic modeling of colistin and imipenem against *in vitro* *Pseudomonas***

2 ***aeruginosa* biofilms**

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26 **ABSTRACT**

27 **Introduction**

28 Antibiotic treatment of chronic biofilm-associated infections can be challenging. Characterization of pharmacokinetic-  
29 pharmacodynamic (PK-PD) relationships for biofilm-associated infections may be relevant to inform the design of  
30 antibiotic treatment regimens for biofilm-associated infections. To this end, we aim to develop a mathematical PK-PD  
31 model for planktonic and biofilm bacterial infections and demonstrate how PK-PD simulations can be used to design  
32 optimized dosing schedules, using imipenem and colistin as proof-of-concept examples.

33 **Methods**

34 Pharmacodynamic models were developed using time-kill assay data from planktonic and alginate-bead biofilm cultures  
35 of *Pseudomonas aeruginosa* exposed to imipenem or colistin. The PD models were coupled to population PK models  
36 for plasma and epithelial lining fluid (ELF) to translate PD relationships for clinical dosing schedules and PK-PD indices.

37 **Results**

38 The developed models incorporated sensitive and resistant bacterial subpopulations and were able to adequately  
39 capture the observed time-kill data. Simulation studies identified differences in suppression of bacterial growth dynamics  
40 for multiple clinical intravenous and inhalation-based treatment regimens and were used to infer biofilm-specific PK-PD  
41 indices associated with ELF target site concentrations.

42 **Conclusion**

43 In conclusion, we demonstrate the utility of mathematical modeling for the characterization of PK-PD relationships  
44 underlying time-kill kinetic profiles in biofilm-associated infections and their utility in translating experimental findings to  
45 inform the optimization of clinical dosing schedules.

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48

49 **INTRODUCTION**

50 Chronic lung infections associated with cystic fibrosis (CF) are typically associated with bacterial biofilms and respond  
51 poorly to antibiotic therapy [1–3]. Patients with chronic CF lung infections may receive long-term antibiotic therapy  
52 including daily nebulized antibiotic treatment and systemic antibiotic treatment during acute exacerbations [4, 5]. Biofilm-  
53 associated pathogens often show reduced antibiotic sensitivity compared to their planktonic form, mediated by several  
54 mechanisms [6]. In addition, the antimicrobial target-site concentrations may differ significantly from plasma  
55 concentrations, i.e., the lungs in case of chronic CF lung infections [7, 8]. There is a need to further optimize antibiotic  
56 dosing schedules for the treatment of biofilm-associated chronic lung infections in CF patients.

57  
58 A rational treatment design for biofilm-associated bacterial infections requires information on the antibiotic  
59 concentration-time profile at the site of infection (pharmacokinetics, PK) and the observed relationship between drug  
60 exposure and response of bacterial pathogens (pharmacodynamics, PD). In terms of PD, different mechanisms  
61 contribute to the decreased susceptibility of biofilm bacteria [9]. For example, the formation of extracellular matrix  
62 protects the inside bacteria from the attack of immune system and poses a diffusion barrier against antibiotics. In addition,  
63 bacterial pathogens may develop resistance, i.e., resilience against antibiotic treatment mediated through transient  
64 adaptation or non-transient genetic mutations.

65  
66 Antimicrobial PK-PD relationships can be characterized using experimental *in vitro* and *in vivo* models. Although static  
67 *in vitro* assays such as MIC or MBIC are useful to obtain quick insight into antimicrobial sensitivity, they are evaluated  
68 at a single time point, for example, 24 h, and do not provide information on dynamic responses such as the emergence  
69 of transient or non-transient antimicrobial resistance [10]. In contrast, *In vitro* and *in vivo* time-kill assays enable  
70 characterization of the time course of bacterial response to antimicrobial agents [11–13], providing essential information  
71 about pathogen-associated PD relationships.

72  
73 Mathematical mechanism-based PD models are useful tools in quantitatively characterizing the bacterial growth and kill  
74 dynamics determined by time-kill assays. Such mechanism-based PD models support systematic testing of hypotheses  
75 that may explain observed pharmacodynamic responses with respect to delays (e.g., due to drug diffusion), differences  
76 in growth rates of bacterial subpopulations, and the shape of concentration-effect relationships [14]. More importantly,  
77 when PD models are coupled to population PK models that predict antimicrobial concentration-time profiles in patients  
78 [13, 15, 16], the efficacy of clinical dosing schedules can be evaluated to assess alternative optimal dosing regimens.  
79 Most antimicrobial PK-PD models have focused on planktonic bacterial pathogens, lacking attention to biofilm-  
80 associated pathogens [17]. To optimize the dosing schedules for biofilm-associated infections, the characterization of  
81 PK-PD relationships for biofilm-associated infections is necessary.

82  
83 Here, we aim to demonstrate the utility of mathematical PK-PD modeling for the analysis of experimental biofilm time-  
84 kill studies to ultimately guide the optimization of dosing schedules for biofilm-associated infections. We focus on  
85 imipenem and colistin for the treatment of the CF-associated pathogen *P. aeruginosa*, as proof of concept. We  
86 specifically aim to (1) develop PD models for imipenem and colistin using data generated from *in vitro* time-kill studies  
87 in planktonic and alginate-bead biofilm experiments [18, 19] and (2) pair the developed models to population PK models  
88 for plasma and lung concentrations to explore and evaluate dosing schedules and PK-PD targets for biofilm-associated  
89 infections, compared to planktonic infections.

90

91 **METHODS**

92 **Time-kill studies**

93 Previously published time-kill studies of *P. aeruginosa* PAO1 planktonic and alginate bead biofilm cultures exposed to  
94 imipenem or colistin were used for mathematical model development [18, 19]. Briefly, the inoculum for both planktonic  
95 and alginate bead experiments was  $10^6$  CFU/mL in lysogeny broth medium. Beads (50-100  $\mu$ m) were produced by  
96 embedding *P. aeruginosa* in seaweed alginate [19]. For colistin, both planktonic and alginate bead biofilm cultures were  
97 exposed to colistin at concentrations of 0-256 mg/L for 24 hours. For imipenem, planktonic cultures were tested against  
98 imipenem at concentrations of 0-32 mg/L for 24 hours, while for the alginate bead biofilm experiments, additional  
99 concentrations up to 2048 mg/L were included (Table S1). The studied concentrations covered a relatively wide efficacy  
100 range. Samples were taken for CFU quantification at 0, 1, 2, 4, 8, 12 and 24 hours post antibiotic exposure.

101

102 **Mathematical model development**

103 Ordinary differential equation (ODE)-based compartmental models were developed to describe the bacterial growth and  
104 kill dynamics in planktonic and biofilm cultures. The models included subpopulations of sensitive (S) and resistant (R)  
105 bacteria, where resistant bacteria were assumed to reflect a bacterial subpopulation with reduced sensitivity. Colony  
106 forming units (CFU) data were  $\log_{10}$ -transformed prior to the analysis. Models for planktonic and biofilm bacteria were  
107 developed separately. Log-transformed predictions were used to estimate the parameters that maximized the log-  
108 likelihood.

109

110 We incorporated natural growth kinetics, the net growth of bacteria in absence of antibiotic, for planktonic and biofilm  
111 cultures. A capacity-limited growth model was used (Eq. 1), including parameters for the maximum bacterial density  
112 ( $B_{max}$ ), and a first-order net growth rate ( $k_{gs}$ ), with a starting bacterial density (CFU/mL) of  $B_0$ .

$$\frac{dS}{dt} = \left(1 - \frac{S + R}{B_{max}}\right) \cdot k_{gs} \cdot S \quad (1)$$

113

114 Drug concentration-effect functions evaluated included linear (Eq. 2) and (sigmoid)  $E_{max}$  functions (Eq. 3), separately,  
115 for each individual subpopulation (i.e., S, R). Antibiotic concentration-effect models (i.e., linear or Emax) were defined  
116 as follows:

$$E_{drug} = slope \cdot C_{drug} \quad (2)$$

$$E_{drug} = \frac{E_{max} \cdot C_{drug}^\gamma}{EC_{50}^\gamma + C_{drug}^\gamma} \quad (3)$$

117

118 where *slope* is the linear kill rate constant,  $E_{max}$  represents the maximum kill effect,  $EC_{50}$  indicates the drug  
119 concentration at which 50% of the maximum effect is obtained, and  $\gamma$  is the steepness of the concentration-effect  
120 relationship factor. Since drug concentration-effect models may vary across drugs, bacterial subpopulations and  
121 lifestyles (i.e., planktonic or biofilm), separate drug effect models were considered for each of these conditions.

122

123 We investigated the occurrence of an effect delay in biofilm cultures, e.g., which could for example be explained by  
124 retarded drug diffusion into the biofilm. Such a delay would account for a possible discrepancy between the  
125 experimentally used drug concentration ( $C_{drug_{exp}}$ ) and the effective drug concentration that exerted pharmacodynamic  
126 effect on bacteria. The delay was described using a transit model (Eq. 4), with a first-order transit rate constant  $k_{tr}$ ,  
127 including  $n$  transit compartments. The concentration in the last transit compartment ( $C_{drug_{(n)}}$ ) represented the

128 concentration driving the effect. Mean transit time (*MTT*), the average time spent by drugs traveling from the first transit  
129 compartment to the last compartment, was calculated with  $k_{tr}$  and  $n$  (Eq. 5).

$$\frac{dC_{drug(1)}}{dt} = k_{tr} \cdot C_{drug_{exp}} - k_{tr} \cdot C_{drug_1}$$

...

(4)

$$\frac{dC_{drug(n)}}{dt} = k_{tr} \cdot C_{drug_{(n-1)}} - k_{tr} \cdot C_{drug(n)}$$
$$MTT = \frac{n+1}{k_{tr}}$$

(5)

130

131 We incorporated a drug-induced transition rate  $k_{sr}$  to describe the transfer of bacteria from S to R state, which only  
132 occurred if an antibiotic is present (Eq. 6-7), for both planktonic and biofilm bacteria. Initially, all bacteria were assumed  
133 to be in the sensitive (S) state. First-order growth rates for S and R populations were estimated separately. Drug-induced  
134 killing effect was described using a first-order rate process for each subpopulation separately.

$$\frac{dS}{dt} = \left(1 - \frac{S+R}{B_{max}}\right) \cdot k_{gs} \cdot S - k_{sr} \cdot S - E_{drug,S} \cdot S ; S(0) = B_0 \quad (6)$$

$$\frac{dR}{dt} = \left(1 - \frac{S+R}{B_{max}}\right) \cdot k_{gr} \cdot R + k_{sr} \cdot S - E_{drug,R} \cdot R ; R(0) = 0 \quad (7)$$

135

136 An additive error model for log-transformed data was used to estimate residual unexplained variability. Bacterial counts  
137 below the lower limit of quantitation (LLOQ, defined as 10 CFU/mL) were handled using the M3 method [20].

138

### 139 **Sensitivity analysis**

140 To determine the relative importance of model parameters estimated, a sensitivity analysis was performed for each  
141 parameter ( $p$ ) in the final model. The local sensitivity  $Sens$  was evaluated using the relative change in the area under  
142 time-CFU curve (AUC) between 0 and 24 hours, in relation to the relative change of parameters (Eq. 8) [21].

$$Sens = \frac{\Delta AUC}{AUC} \div \frac{\Delta p}{p} \quad (8)$$

143

### 144 **Dosing regimen simulations**

145 We implemented published population PK models for intravenous and inhaled colistin and intravenous imipenem [22,  
146 23] to predict the antibiotic concentration-time profiles in plasma and epithelial lining fluid (ELF) in the lung. 1000  
147 individuals were simulated to take the inter-individual variability into account. As patient covariates (i.e. body weight and  
148 creatinine clearance) acted as significant factors in the prediction of the concentration profiles of imipenem, a virtual  
149 population generated from the NHANES copula (<https://cocosim.lacdr.leidenuniv.nl/>) was used as the input to obtain  
150 realistic covariates combinations and simulation results [24, 25]. For colistin, we studied intravenous administration of  
151 160 mg (2 MIU) every 8 hours of colistimethate sodium (CMS), the inactive prodrug of colistin, 720 mg (9 MIU) CMS  
152 every 24 h, and inhalation of 160 mg (2 MIU) CMS every 8 hours, consistent with recommended clinical dosing regimens  
153 [26]. For imipenem, we simulated clinical tolerable doses [4]: 250, 500 and 1000 mg every 6 hours intravenously. The  
154 PK simulations for ELF antibiotic concentrations were linked to our PD models for planktonic and biofilm bacteria, to  
155 study the relative difference in bacterial dynamics under different dosing schedules for planktonic and biofilm-associated  
156 infections. Protein concentrations in ELF were considered negligible.

157

## 158 **PK-PD target analyses**

159 To identify PK-PD indices for colistin and imipenem relating to planktonic and biofilm bacteria, we simulated extensive  
160 dose fractionation studies, using a wide dose range for a duration of 24 hours, similar to the method used by a previous  
161 study [27]. For each dosing schedule, we computed the PK-PD indices, including the maximum ELF concentration of  
162 drug over the minimum inhibitory concentration ( $C_{\max}/\text{MIC}$ ) and over the minimum biofilm inhibitory concentration  
163 ( $C_{\max}/\text{MBIC}$ ), area under the concentration-time curve for drug over the MIC (AUC/MIC) and over the MBIC (AUC/MBIC),  
164 and the fraction of time when the concentration was above the MIC ( $f_{T>\text{MIC}}$ ) and above the MBIC ( $f_{T>\text{MBIC}}$ ). The PK profiles  
165 were used to predict the treatment response in planktonic and biofilm bacterial infections using the established PD  
166 models. For each bacterial lifestyle against each drug, we regressed PK-PD indices against the change of bacterial  
167 density ( $\log_{10} \text{CFU/mL}$ ) after 24 hours of treatment using a sigmoidal  $E_{\max}$  equation, and the fit was evaluated by  
168 calculating the  $R^2$  value, to select the PK-PD indices that could best predict the killing effect after 24 hours (e.g. -1 and -  
169 2  $\log_{10}$  kill).

## 170

## 171 **Software and model selection**

172 Model development was performed using non-linear mixed fixed effects modeling software NONMEM 7.5. Graphical  
173 visualizations, simulations and interpretations were performed using R 4.3.2. Model selection was guided by successful  
174 minimization, successful covariance step, objective function value (OFV, 5% significance level), Akaike information  
175 criterion (AIC), precision of parameters' estimates (relative standard errors < 30%), goodness-of-fit plots, and visual  
176 predictive checks [28].

## 177

## 178 **RESULTS**

### 179 **Mathematical model development**

180 Both colistin and imipenem showed a concentration-dependent killing effect against planktonic and biofilm-embedded  
181 *P. aeruginosa*. Regrowth was observed after approximately 4 hours in both models when exposed to colistin and 4-8  
182 hours when exposed to imipenem (**Figure S1**). The time-kill kinetics of planktonic and alginate bead biofilm cultures  
183 were described separately using pharmacodynamic models for colistin (**Figure 1A**) and imipenem (**Figure 1B**). The  
184 models adequately captured the observed bacterial growth- and kill-profiles (**Figure 2**). Model parameters were  
185 estimated precisely, with relative standard errors  $\leq 20\%$  (**Table 1**).

186

187 Emax models best described the drug concentration-effect relationship for colistin on the biofilm resistant bacteria  
188 population and imipenem on the planktonic sensitive bacteria population, while linear models were identified for all other  
189 drug effect relationships.  $E_{\text{drug}}$  of colistin and imipenem on S and R bacteria populations demonstrated comparable  
190 efficacy for planktonic bacteria across drug concentrations and showed less than 0.5 fold differences at the highest  
191 tested concentrations (**Figure 3**, left panel). However, significant differences were observed in  $E_{\text{drug}}$  between sensitive  
192 and resistant biofilm populations, with the difference increasing for higher drug concentrations (**Figure 3**, right panel),  
193 suggesting increased resistance in the biofilm population compared to planktonic populations.

194

195 For both colistin and imipenem, we estimated the drug-specific rate of diffusion retardation into the biofilm. One transit  
196 compartment was implemented for colistin, while three transit compartments were employed for imipenem. We also  
197 evaluated models with 0 to 4 transit compartments, and found 1 and 3 transit compartment(s) fitted the colistin and  
198 imipenem data best. Parameter estimates ( $k_{tr}$  and  $n$ ) revealed that imipenem exhibited a slightly longer MTT (3.4 hours)  
199 compared to colistin (3.0 hours). Local sensitivity analysis identified the most sensitive parameters driving the predicted

200 response for each model, with resistant subpopulation-related parameters (i.e.  $slope_R$ ,  $k_{sr}$ ,  $E_{max,R}$  and  $EC_{50,R}$  )  
201 demonstrating wide influence across both studied drugs (**Figure S2**).

203 **Dosing regimen simulations**

204 We simulated the treatment outcome of standard and adapted dosing schedules of colistin (**Figure 4**) and imipenem  
205 (**Figure 5**) against planktonic and biofilm-associated *P. aeruginosa* lung infections, using the PK-PD models (i.e.,  
206 developed PD models coupled with clinical population PK models).

207  
208 For colistin, our simulations showed that under the treatment of 160 mg (2 MIU) every 8 hours (**Figure 4A**) and 720 mg  
209 (9 MIU) every 24 hours (**Figure 4B**), colistin was insufficient for patients with biofilm infections. An inhalation dose of  
210 160 mg (2 MIU) resulted in a high drug concentration at the ELF, leading to a successful eradication of both planktonic  
211 and biofilm bacteria (**Figure 4C**).

212  
213 For imipenem, a clear dose-dependent killing effect was found. For planktonic bacterial infection, both 250 mg and 500  
214 mg every 6 hours (**Figure 5A, 5B**) could suppress the growth of biofilm cells yet were unable to fully eliminate the  
215 infections within 24 hours; 1000 mg every 6 hours (**Figure 5C**) could efficiently kill the bacteria.

216  
217 **PK-PD indices**

218 We investigated the PK-PD indices for the prediction of treatment response of planktonic and biofilm bacteria infections  
219 by performing intravenous dose fractionation studies (**Figure 6**), based on the target site drug concentration in the ELF.  
220 We found that AUC/MIC ( $R^2=0.995$  for colistin;  $R^2=0.997$  for imipenem) and AUC/MBIC ( $R^2=0.956$  for colistin;  $R^2=0.997$   
221 for imipenem) were best correlated with the observed effect for both planktonic and biofilm bacterial infections for both  
222 drugs. For planktonic bacteria, we found that for a CFU change from  $-1 \log_{10}$  to  $-2 \log_{10}$ , the AUC/MIC target for colistin  
223 and imipenem increased from 46 to 48, and from 123.7 to 130.6, respectively. For biofilm bacteria, a CFU change of  $-1 \log_{10}$   
224 at 24 hours corresponded to 567.1 and 3 for the AUC/MBIC target of colistin and imipenem, respectively.  
225 However, no targets of AUC/MBIC were able to be derived for  $-2 \log_{10}$  CFU change due to insufficient drug effect at  
226 tolerable intravenous dosages (**Table 2**). The treatment outcome under simulated dosing regimens aligned with the  
227 expected response based on the derived targets. For example, 160 mg (2 MIU) colistin every 8 hours (AUC/MIC = 39)  
228 did not achieve the PK-PD targets for planktonic infection and failed to eradicate the bacteria, while 720mg every 24  
229 hours (AUC/MIC = 70) reached the targets and eradicated the bacteria efficiently.

230  
231 In terms of PK-PD indices based on plasma drug concentration, AUC/MIC ( $R^2=0.113$ ) and AUC/MBIC ( $R^2=0.171$ ) were  
232 best correlated with the change of bacteria count for colistin, while AUC/MIC ( $R^2=0.997$ ) and AUC/MBIC ( $R^2=0.997$ )  
233 were still most predictive of the effect for imipenem (**Figure S3**). A comparison between ELF-based (**Figure 6**) and  
234 plasma-based PK-PD indices (**Figure S3**) revealed an increased variation in responses to colistin and a consistent  
235 correlation between PK-PD indices and treatment effect for imipenem.

236  
237 **DISCUSSION**

238 We developed a pharmacodynamic model to characterize growth and kill dynamics from *in vitro* biofilm assays, focusing  
239 on the pathogen *P. aeruginosa* treated with colistin or imipenem, as a proof-of-concept. Prior knowledge of patient-  
240 specific antibiotic PK was integrated into the modeling framework and applied to investigate the effect of different dosing  
241 regimens, and the predictivity of different drug exposures (PK-PD indices) for bacterial response was assessed in clinical  
242 settings.

243

In this study, we derived models for different drugs, i.e., colistin and imipenem, as well as bacterial lifestyles, i.e., planktonic cells and biofilms. This model-based data-driven strategy enabled the evaluation of hypotheses with respect to differences in pharmacodynamic responses of planktonic versus biofilm cells.  $E_{max}$  models were identified for only two concentration-effect relationships while for the rest a simple linear model was identified, likely due to insufficient data availability, especially for high drug concentrations. The developed PD models facilitated the comparison of drug-, biological system- or experiment-specific parameters that ultimately characterize the observed response, providing insight into the underlying pharmacological basis of the antibiotic response. We identified distinct factors that contribute to increased resistance of biofilm cells compared to planktonic cells against both colistin and imipenem. First of all, biofilm cells exhibited slower growth rates (0.615 and 0.441  $h^{-1}$ ) compared to planktonic cells (0.807 and 0.944  $h^{-1}$ ), consistent with the literature [29, 30]. These reduced growth rates reflect biofilm cells' adaptation to environments with limited nutrients and oxygen, which requires lower metabolic activity for survival. Secondly, a delay in antibiotic drug effect for biofilms, as represented by a transit model, was found for both colistin and imipenem against biofilm bacterial infections. This delay can be explained by the diffusion barrier presented by the extracellular matrix secreted by biofilm cells, the components of which could interact with antibiotics and slow their delivery. For example, the negatively charged polysaccharides could bind to positively charged colistin and impede penetration into biofilm [31]. Thirdly, compared to planktonic resistant species, a reduced susceptibility of biofilm resistant species was found (**Figure 3**). This discrepancy might be relevant to further physiological adaptations in biofilm cells compared to planktonic cells [32].

261

Coupling PD models with clinical population PK models enabled us to make translational predictions about the expected effects of bacterial growth/kill dynamics in patients. We predicted for colistin that dosing of 2 MIU per inhalation q 8 h shows a better biofilm-eradicating effect in lung infection patients compared to intravenous treatment of 2 MIU q 8 h and 9 MIU q 24 h. This result is in line with previous studies in COPD patients and ICU patients with pulmonary infections after lung transplantation [33, 34]. The regrowth of both planktonic and biofilm growing *P. aeruginosa* under exposure to colistin (planktonic: 1mg/L - 4 mg/L, biofilm: 1 mg/L - 64 mg/L) (**Figure 2A**) is probably due to the adaptive response that involved modifications of lipopolysaccharide (LPS) in the outer membrane, which prevents penetration of colistin [35–37]. Imipenem showed less predicted efficacy against planktonic and biofilm bacterial infections under standard clinical dosing, which might be partially because *P. aeruginosa* can readily develop adaptive responses (adaptive resistance) to imipenem and regrow under exposure to imipenem (**Figure 2B**) via upregulating production of alginate and AmpC  $\beta$ -lactamase [38, 39]. Although clinical implications of these model-based predictions should be treated with caution, they could provide additional insights into the differences observed in preclinical *in vivo* or *in vitro* studies, for instance when evaluating and comparing treatment regimens.

275

ELF concentration-based AUC/MIC and AUC/MBIC were identified as the PK-PD indices that could best predict the treatment outcome for both colistin and imipenem based on *in silico* dose fractionation simulations. A study using a murine infection model identified serum AUC/MIC and AUC/MBIC as the best PK-PD indices of colistin for planktonic and biofilm infections, yet for imipenem  $f_{T>MIC}$  and  $f_{T>MBIC}$  were found to best predict the efficacy for planktonic cell and biofilm infections [40]. Plasma samples are more readily measurable than lung ELF concentrations in patients, thus, we examined the feasibility of using plasma concentration for the derivation of PK-PD indices. Plasma concentration-based PK-PD indices of imipenem were found to be more predictive compared to those of colistin. For both colistin and imipenem, the same PK-PD indices (AUC/MIC and AUC/MBIC) were identified based on plasma concentration and ELF concentrations. Yet for colistin, indices (AUC/MIC and AUC/MBIC) identified with ELF concentrations ( $R^2=0.995, 0.956$ ) got less informative when replaced with plasma concentrations ( $R^2=0.113, 0.171$ ). This is because of colistin's bi-directional transfer between plasma and ELF compartments in the population PK model [22], which leads to a non-linear

286

287 relationship between plasma and ELF concentrations. The consistency for imipenem PKPD indices stems from its linear  
288 relationship between plasma and ELF concentration characterized in the population PK model [23]. Given that this  
289 speculation was based on simulations, further validation with real-world data is needed.

290

291 In the current study, pharmacodynamic models were developed based on bacteria data exposed to static concentrations  
292 of antibiotics measured up to 24 hours, which may not reflect the clinical reality for longer antibiotic treatment and time-  
293 varying antibiotic concentration. Conducting longer-term time-kill assays that mimic clinical treatments, such as using  
294 CDC biofilm reactors with humanized dynamic exposure, may help overcome the limitation [41, 42]. Indeed, several  
295 studies have employed CDC biofilm reactor model to investigate the efficacy of antibiotics against biofilms [30–32].

296

297 Our analysis demonstrates how a semi-mechanistic pharmacodynamic modeling approach can facilitate further  
298 pharmacological interpretation of *in vitro* biofilm infection models, through the separation of drug- and biological system  
299 (e.g. planktonic or biofilm)-specific parameters, in line with related publications describing similar semi-mechanistic  
300 mathematical models reported for *in vitro* flow cell models and an *in vivo* rat lung infection model [43–45]. We expect  
301 that semi-mechanistic modeling approaches are relevant to allow the simultaneous integration of multiple pertinent  
302 pharmacodynamic readouts, e.g. CFU counts, biofilm mass, and metabolic activity.

303

304 In conclusion, we report a proof-of-concept analysis of the utility of mathematical pharmacodynamic modeling of *in vitro*  
305 biofilm time-kill assays and its integration with clinical PK models to derive translational predictions about expected  
306 effects in patients.

307

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310

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**Table 1. Parameter estimates of the pharmacodynamic model for imipenem and colistin for *in vitro* planktonic and biofilm time-kill assays.**

Parameter	Description	Units	Colistin (RSE%)		Imipenem (RSE%)	
			Planktonic	Biofilm	Planktonic	Biofilm
$k_{gs}$	Maximal growth rate of sensitive bacteria	$h^{-1}$	0.807 (6)	0.615 (7)	0.944 (3)	0.441 (11)
$k_{gr}$	Maximal growth rate of resistant bacteria	$h^{-1}$	3.71 (21)	3.85 (2)	1.76 (4)	0.0614 (7)
$B_0$	Baseline bacterial count	$\log_{10}$ CFU/mL	5.81 (1)	5.45 (3)	5.58 (2)	6.45 (2)
$B_{max}$	Bacterial count in stationary phase	$\log_{10}$ CFU/mL	9.35 (1)	8.85 (2)	9.42 (1)	9.38 (4)
$k_{sr}$	Transfer rate from sensitive bacteria to resistant bacteria	$-\log_{10} h^{-1}$	3.96 (16)	4.27 (2)	3.74 (1)	3.11 (9)
$Slope_s$	Linear coefficient for drug effect in sensitive bacteria	L/mg*h	1.29 (3)	1.21 (7)	-	0.149 (11)
$Slope_r$	Linear coefficient for drug effect in resistant bacteria	L/mg*h	0.86 (20)	-	0.279 (5)	0.0008 (20)
$E_{maxs}$	The maximal achievable kill rate constant for sensitive bacteria	$h^{-1}$	-	-	9.28 (1)	-
$EC_{50s}$	Concentration that results in 50% of $E_{max}$ for sensitive bacteria	mg/L	-	-	19.1 (1)	-
$Hill_s$	Hill coefficient for sensitive bacteria		-	-	0.285 (4)	-
$E_{maxr}$	The maximal achievable kill rate constant for resistant bacteria	$h^{-1}$	-	4.06 (2)	-	-
$EC_{50r}$	Concentration that results in 50% of $E_{max}$ for resistant bacteria	mg/L	-	0.416 (4)	-	-
$Hill_r$	Hill coefficient for resistant bacteria		-	0.399 (3)	-	-
$k_{tr}$	Distribution rate constant between transit compartments	$h^{-1}$	-	0.66 (3)	-	1.19 (8)
$N$	Number of transit compartments	-	-	1	-	3
RES	Additive residual error in bacteria experiment ( $\log_{10}$ scale)	-	0.364 (8)	0.564 (7)	0.394 (6)	0.898 (6)

RSE, relative standard error; RES, residual variance error.

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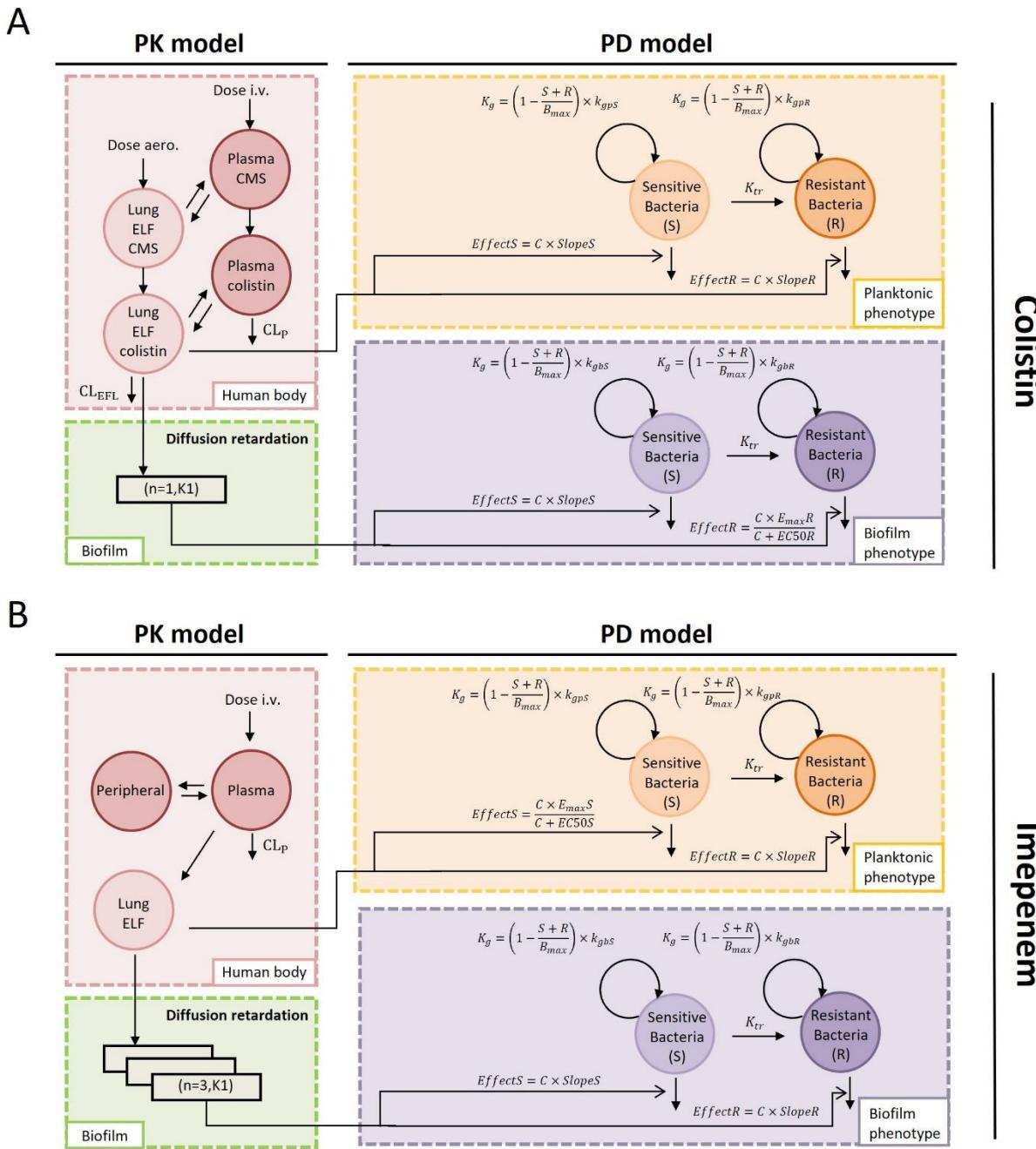
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**Table 2. ELF-based PK-PD target values derived for colistin and imipenem at -1 and -2 log10 unit kill using simulated dose fractionation studies.**

	Colistin		Imipenem	
	Planktonic	Biofilm	Planktonic	Biofilm
	AUC/MIC	AUC/MBIC	AUC/MIC	AUC/MBIC
	(h)	(h)	(h)	(h)
<b>-1 log10</b>	46	567.1	123.7	3
<b>-2 log10</b>	48	-	130.6	-



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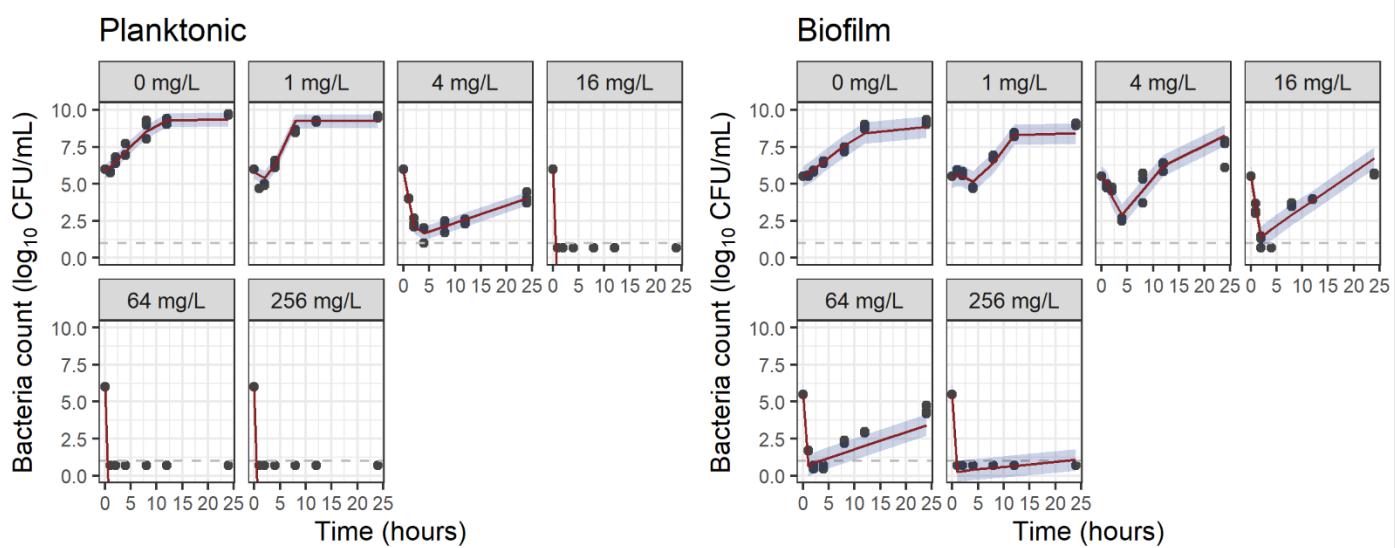
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**Figure 1. Schematic illustration of the pharmacokinetic-pharmacodynamic model structures.** Model structures for colistin and imipenem included the pharmacodynamic models describing the time-kill kinetics in planktonic and alginate bead biofilm models, in combination with clinical pharmacokinetic models for plasma and lung epithelial lining fluid (ELF) compartments. Separate pharmacodynamic models were developed for biofilm and planktonic bacteria cells for colistin and imipenem.

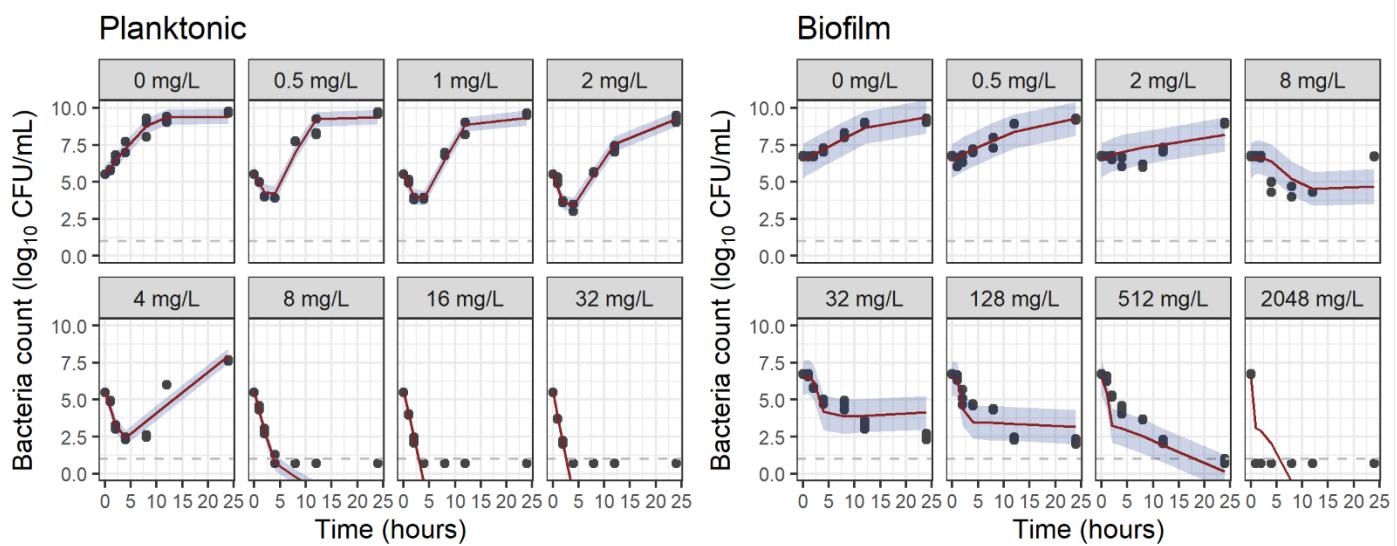
A

### Colistin model



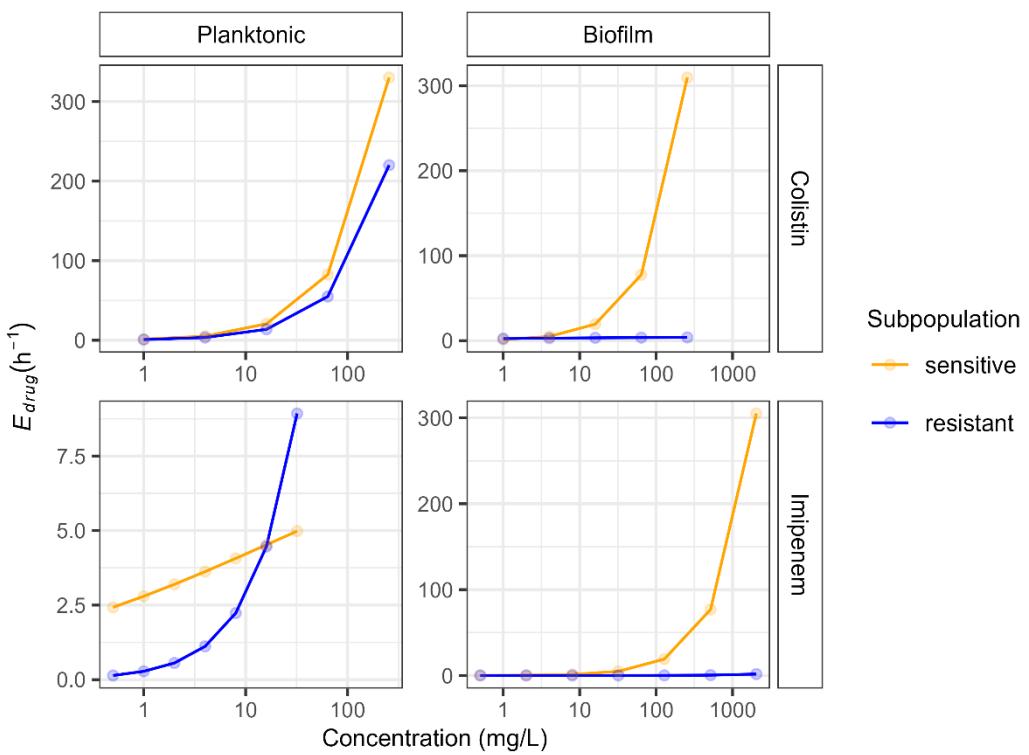
B

### Imipenem model



**Figure 2. Visual predictive check of the pharmacodynamic models for colistin (A) and imipenem (B).** The black points are the observed bacterial count data (Log<sub>10</sub> CFU); the red lines represent the median values of model predictions; The blue areas are the 10<sup>th</sup> to 90<sup>th</sup> percentile area of the model predictions. Observations below the quantification limit (gray dashed line) were displayed as half of the quantification limit.

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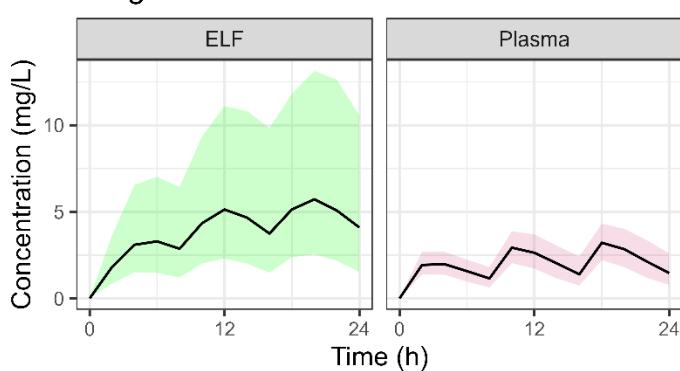
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**Figure 3. Drug effect comparison.** The intermediate variable,  $E_{drug}$ , was computed for each drug concentration studied in the time-kill assay using estimated parameters derived from drug concentration-effect models. Orange and blue lines represent exposure-response curves of sensitive and resistant subpopulations, respectively. Points on lines indicate the drug effect at the concentrations studied in time-kill experiments.

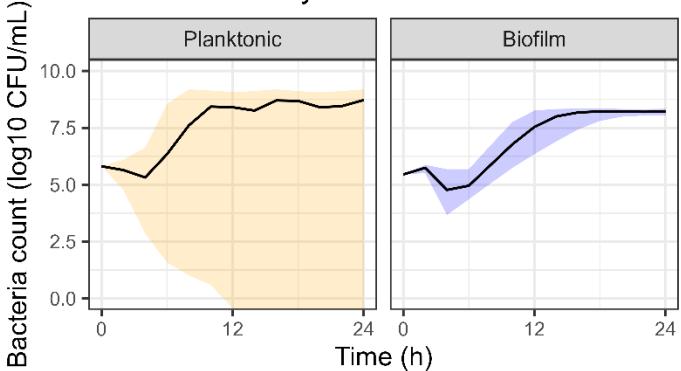
A

i.v. Colistin 160mg q8h 24h

Drug concentration



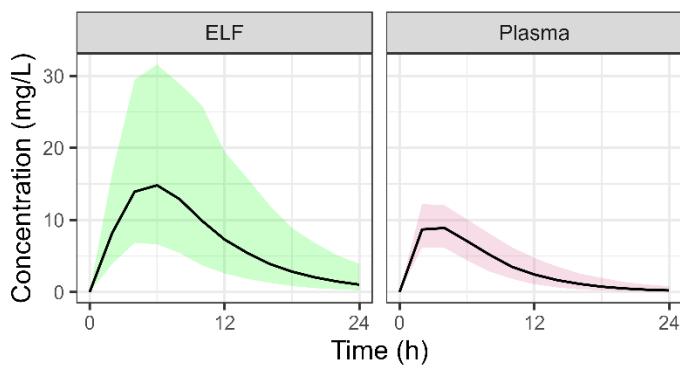
Bacteria density



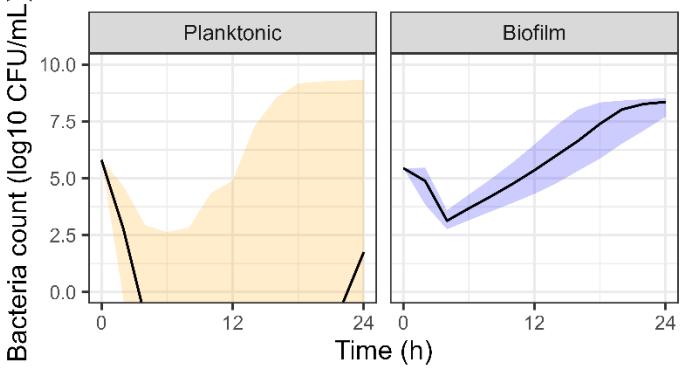
B

i.v. Colistin 720mg q24h 24h

Drug concentration



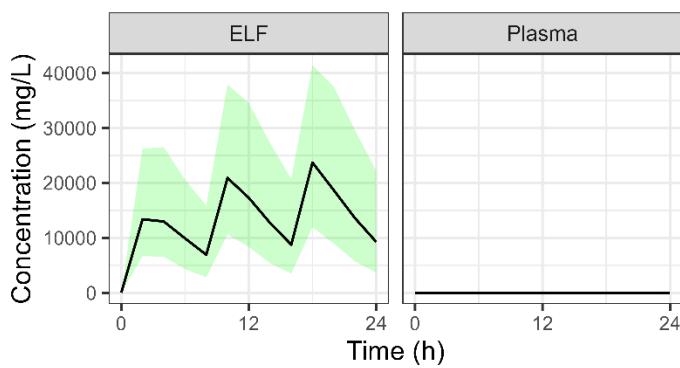
Bacteria density



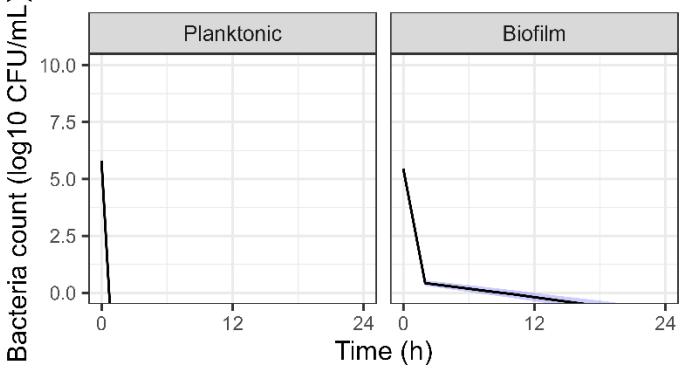
C

ae. Colistin 160mg q8h 24h

Drug concentration



Bacteria density



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**Figure 4. Dosing regimen simulations for colistin.** Dosing regimens were simulated using clinical population pharmacokinetic models depicting the median (lines) and 25<sup>th</sup> and 75<sup>th</sup> percentiles (shaded areas) of drug concentration and bacteria count versus time. The predicted epithelial lining fluid (ELF) concentration was used as input for the pharmacodynamic models. Dosing regimens simulated included intravenous (i.v.) administration of 160 mg (2 MIU) q 8 h (A), 720 mg (9 MIU) q 24 h (B), or aerosol (ae.) inhalation of 160 mg (2 MIU) q 8 h (C).

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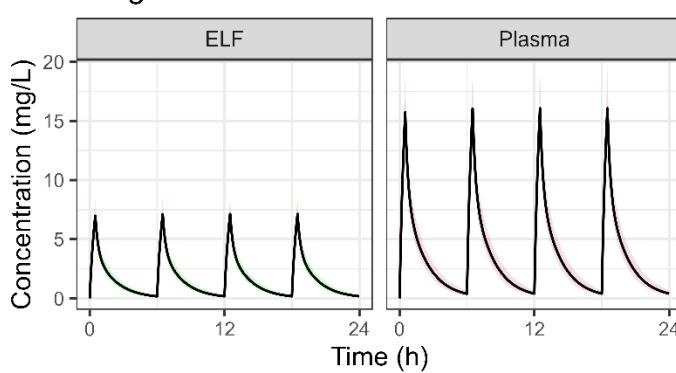
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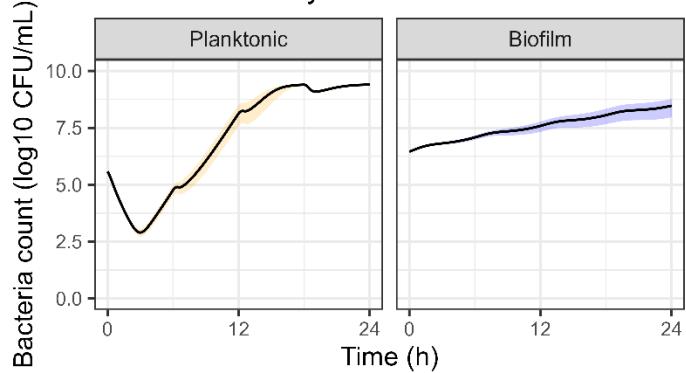
A

i.v Imipenem 250mg q6h 24h

Drug concentration



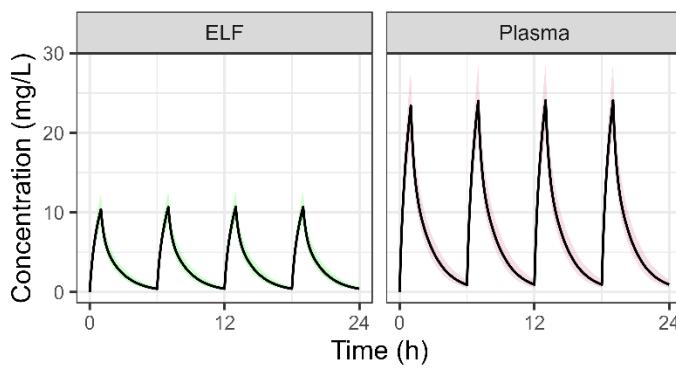
Bacteria density



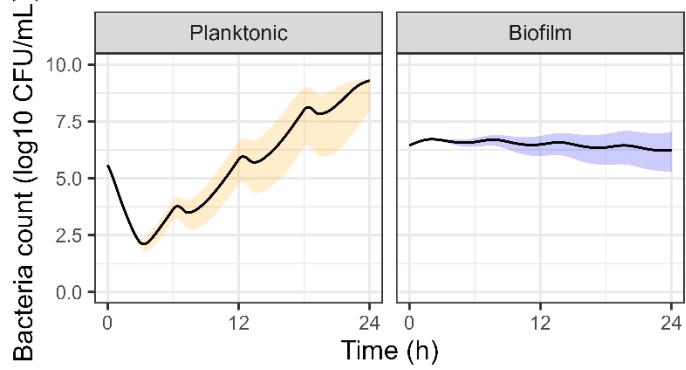
B

i.v Imipenem 500mg q6h 24h

Drug concentration



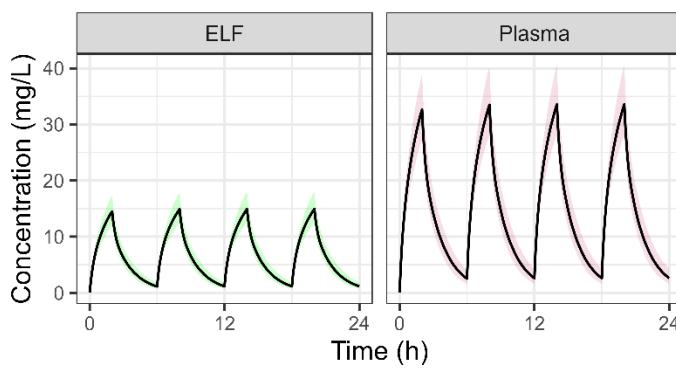
Bacteria density



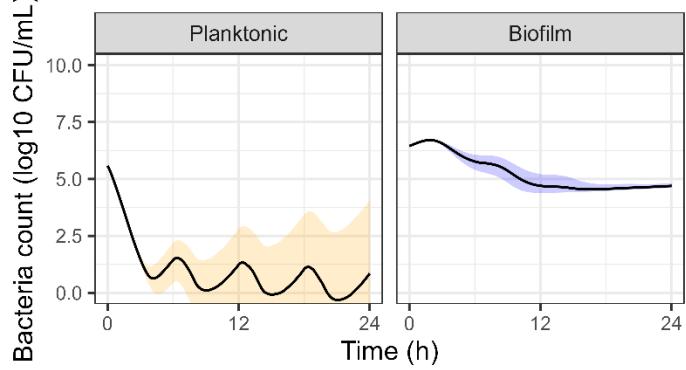
C

i.v Imipenem 1000mg q6h 24h

Drug concentration

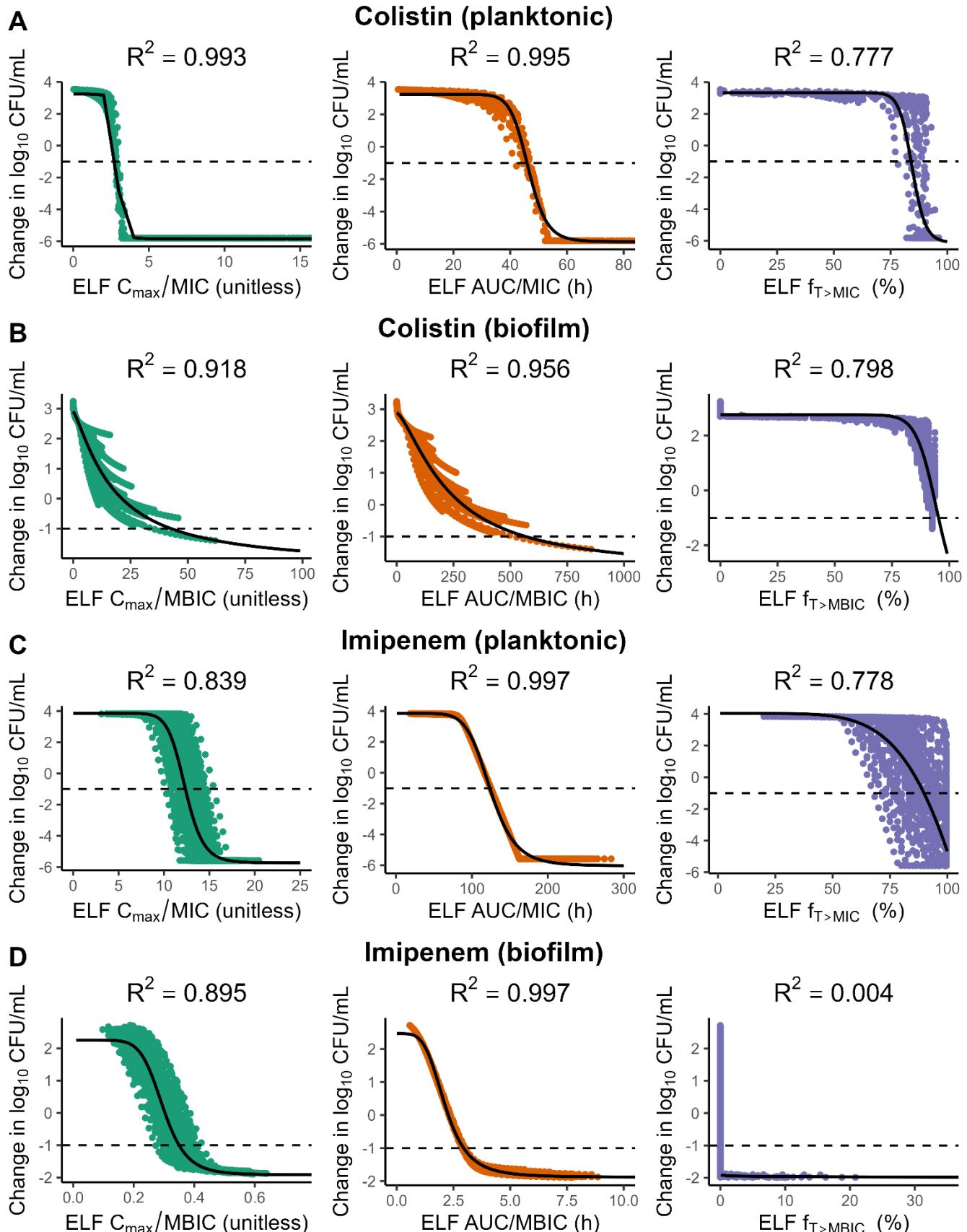


Bacteria density



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485 **Figure 5. Dosing regimen simulations for imipenem.** Dosing regimens were simulated using clinical population  
486 pharmacokinetic models depicting the median (lines) and 25 and 75<sup>th</sup> percentiles (shaded areas) of drug concentration  
487 and bacteria count versus time. The predicted epithelial lining fluid (ELF) concentration was used as input for the final  
488 pharmacodynamic models. Dosing regimens simulated included intravenous (i.v.) administration of 250 mg (A), 500 mg  
489 (B) or 1000 mg (C) every 6 hours.  
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**Figure 6. Pharmacokinetic-pharmacodynamic (PK-PD) target analysis for colistin and imipenem against planktonic and biofilm infections based on epithelial lining fluid (ELF) antibiotic concentrations.** Dose fractionation studies were simulated and resulting ELF concentrations were regressed against the change in model predicted bacterial densities at 24 hours (points) compared to the baseline using a sigmoidal  $E_{max}$  model resulting in optimal model fits (solid lines).