

1 All-optical electrophysiology refines populations of in silico human iPS-CMs for drug
2 evaluation

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4 Running Title: Optically calibrated hiPS-CMs population

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9 Keywords: Computational Methods & Bioinformatics; Ion Channels, Pharmacology &
10 Disease; Cardiac, Smooth & Skeletal Muscle Electrophysiology.

11 Techniques: Electrophysiology; Fluorescence.

12 Abstract

13 High-throughput *in vitro* drug assays have been impacted by recent advances in human induced
14 pluripotent stem cell-derived cardiomyocytes (hiPS-CMs) technology and by contact-free all-
15 optical systems simultaneously measuring action potential (AP) and Ca²⁺ transient (CaTr).
16 Parallel computational advances have shown that *in silico* models can predict drug effects with
17 high accuracy. In this work, we combine these *in vitro* and *in silico* technologies and
18 demonstrate the utility of high-throughput experimental data to refine *in silico* hiPS-CM
19 populations, and to predict and explain drug action mechanisms. Optically-obtained hiPS-CM
20 AP and CaTr were used from spontaneous activity and under pacing in control and drug
21 conditions at multiple doses.

22 An updated version of the Paci2018 model was developed to refine the description of hiPS-
23 CM spontaneous electrical activity; a population of *in silico* hiPS-CMs was constructed and
24 calibrated using the optically-recorded AP and CaTr. We tested five drugs (astemizole,
25 dofetilide, ibutilide, bepridil and diltiazem), and compared simulations against *in vitro* optical
26 recordings.

27 Our simulations showed that physiologically-accurate population of models can be obtained
28 by integrating AP and CaTr control records. Thus constructed population of models predicted
29 correctly the drug effects and occurrence of adverse episodes, even though the population was
30 optimized only based on control data and *in vitro* drug testing data were not deployed during
31 its calibration. Furthermore, the *in silico* investigation yielded mechanistic insights, e.g.
32 through simulations, bepridil's more pro-arrhythmic action in adult cardiomyocytes compared
33 to hiPS-CMs could be traced to the different expression of ion currents in the two.

34 Therefore, our work: i) supports the utility of all-optical electrophysiology in providing high-
35 content data to refine experimentally-calibrated populations of *in silico* hiPS-CMs, ii) offers
36 insights into certain limitations when translating results obtained in hiPS-CMs to humans and
37 iii) shows the strength of combining high-throughput *in vitro* and population *in silico*
38 approaches.

39

40 Significance

41 We demonstrate the integration of human *in silico* drug trials and optically-recorded
42 simultaneous action potential and calcium transient data from human induced pluripotent stem
43 cell-derived cardiomyocytes (hiPS-CMs) for prediction and mechanistic investigations of drug
44 action. We propose a population of *in silico* models i) based on a new hiPS-CM model
45 recapitulating the mechanisms underlying hiPS-CM automaticity and ii) calibrated with all-
46 optical measurements. We used our *in silico* population to predict and evaluate the effects of 5
47 drugs and the underlying biophysical mechanisms, obtaining results in agreement with our
48 experiments and one independent dataset. This work supports the use of high-content, high-
49 quality all-optical electrophysiology data to develop, calibrate and validate computer models
50 of hiPS-CM for *in silico* drug trials.

51

52 Introduction

53 Both, new *in silico* methods and the use of human induced pluripotent stem cell-derived
54 cardiomyocytes (hiPS-CMs) have become increasingly important in tackling the challenge of
55 assessment and prediction of drug effects and their potential cardiotoxicity, as supported by the
56 Comprehensive In Vitro Proarrhythmia Assay (CiPA) initiative (1, 2). Many *in silico* studies
57 on this topic have been published in recent years, showcasing a variety of methodologies,
58 including electrophysiological models of cardiac cells, machine learning algorithms, and a
59 combination of both (3–8). The potential of hiPS-CMs for drug-induced pro-arrhythmia
60 predictions *in vitro* has been shown in many experimental studies (9, 10) despite certain
61 outstanding limitations. Concerns lie with their high inter-lab and inter-batch variability and
62 level of maturity compared to adult cardiomyocytes (11), e.g. spontaneous beating, cell
63 morphology, disorganization of their contractile elements (12), and different ion channel
64 expression (13). Nevertheless, hiPS-CMs represent the best experimental platform to date to
65 study human cardiac electrophysiology and drug action in a rigorous and scalable/high-
66 throughput way. *In silico* models of hiPS-CMs have emerged (14–17) as an invaluable tool to
67 better understand the distinct ionic mechanisms underlying hiPS-CM's drug response (18, 19).
68 The robustness of *in silico* models depends on the amount and the quality of the experimental
69 data used in their calibration and validation. Traditionally, such data have been acquired from
70 a limited number of isolated cells (outside of their multicellular environment), through time-
71 demanding and tedious manual patch-clamp techniques.

72 Limited experimental data present challenges of not being able to capture the genotypical and
73 the phenotypical variability observed in a cell population, which is especially relevant for the
74 highly-variable hiPS-CMs. These challenges have been partially addressed through modelling
75 and data curation. *In silico* population of models approaches have been developed to reflect the
76 wider range of parameters beyond the limited experimental data (20, 21). Database merging
77 has also been used in the desire to expand the experimental data needed to tune the model
78 parameters, e.g. in (19, 22) we merged 6 *in vitro* datasets of action potential (AP) biomarkers
79 to generate a population of *in silico* hiPS-CMs. Using data from different laboratories widen
80 the data variability considerably.

81 On the technology side, the problem of limited experimental data has been tackled by new
82 experimental techniques with increased throughput and amenable to automation, e.g.
83 automated patch-clamp platforms (23, 24) or microelectrode arrays (MEAs) (13). However,
84 these techniques still suffer the limitations of probe-sample physical contact, which limits their
85 performance with hiPS-CMs (25). Contact-free optical recordings overcome these limitations
86 and offer comprehensive characterization. Calcium and contraction-measurement systems
87 have been leveraged for cardiotoxicity testing (26). Ahola et al. (27, 28) developed a video-
88 based contact-free method to quantify the biomechanics of beating hiPS-CMs, by processing
89 simultaneous recording of motion and Ca^{2+} transients (CaTr) from fluorescence videos.
90 However, AP signals represent key aspects of cardiotoxicity responses that may not be captured
91 by field potentials, CaTr or mechanical contractions. All-optical electrophysiology (29, 30)
92 approaches offer contactless interrogation and high-throughput records of voltage and calcium
93 in an attempt to increase information content. Application of these techniques to drug screening
94 with hiPS-CMs have been successfully demonstrated (25, 31, 32), including our OptoDyCE
95 that combines optical pacing and simultaneous optical records of voltage and calcium or
96 contractions. The use of optical systems with hiPS-CMs preparations provides an abundance

97 of *in vitro* data with the potential to provide an excellent basis to construct experimentally-
98 calibrated population of *in silico* hiPS-CMs. The value of such high-content optical recordings
99 of CaTr and AP (without ion channel level data) to constrain *in silico* populations of models
100 remains to be tested.

101 The main goal of this work was to demonstrate the utility of *in silico* simulation trials informed
102 by all-optical cardiac electrophysiology (optically-obtained high throughput measurements of
103 AP and CaTr from hiPS-CMs under spontaneous and optically-triggered conditions) for
104 prediction and mechanistic understanding of drug action. Optically-obtained AP and CaTr
105 measurements are used to guide and improve the design and calibration of a population of *in*
106 *silico* hiPS-CMs. We then test the performance of *in silico* simulation trials with the
107 populations of models against *in vitro* drug trials for 5 reference compounds, both in terms of
108 their consistency and to deepen the mechanistic insights unravelled. In detail: i) We present an
109 improved version of the Paci2018 hiPS-CM model (15), providing improved simulation of the
110 $\text{Na}^+/\text{Ca}^{2+}$ exchanger (INCX) role in sustaining the automaticity of AP. ii) We use high throughput
111 optical measurement of AP, CaTr alone and both to calibrate an *in silico* population of hiPS-
112 CMs models. iii) We challenge this population by applying 5 reference compounds at multiple
113 concentrations, and comparing the results against *in vitro* data, not used for the calibration step.
114 iv) We investigate the mechanisms underlying the different response to bepridil in hiPS-CMs
115 (both *in vitro* and *in silico*) compared to adult cardiomyocytes.

116 Materials and Methods

117 Experimental dataset

118 The experimental dataset consists of AP and CaTr recordings from hiPS-CMs syncytia (CDI
119 iCell² cardiomyocytes) obtained with the all-optical OptoDyCE system (25) in a 384-well plate
120 format at room temperature (21°C) and with extracellular concentrations $\text{Na}_0 = 135.0$, $\text{K}_0 =$
121 5.4 and $\text{Ca}_0 = 1.33\text{mM}$, in both paced and non-paced conditions. Recordings were performed
122 in control conditions (0.1% DMSO) and following application of 5 reference compounds:
123 astemizole (antihistamine), dofetilide (antiarrhythmic agent, class III), ibutilide
124 (antiarrhythmic agent, class III) bepridil (antiarrhythmic agent, class IV) and diltiazem
125 (antiarrhythmic agent, class IV).

126 Control recordings were performed on 10 plates (384-well format). Voltage and calcium-
127 derived biomarkers were obtained from 5 independent multicellular samples per plate (each
128 sample having at least 200 cells). The following biomarkers were considered: AP and CaTr
129 cycle length (AP CL and CaTr CL), duration at 30%, 50% and 90% of AP repolarization
130 (APD_{30} , APD_{50} and APD_{90}) and of CaTr decay (CTD_{30} , CTD_{50} , CTD_{90}), AP and CaTr
131 triangulation ($\text{AP Tri}_{90-30} = \text{APD}_{90} - \text{APD}_{30}$ and $\text{CaTr Tri}_{90-30} = \text{CTD}_{90} - \text{CTD}_{30}$) and CaTr time from
132 CaTr onset to peak (CaTr $t_{\text{Rise}_{0,\text{peak}}}$). Each measurement was characterized by its mean value
133 (mean) and its standard deviation (SD) over a variable number of beats for each multicellular
134 sample. Some acquisitions failed, and were discarded from the dataset, leading to a total of 42
135 control non-paced and 49 control paced multicellular samples, thus integrating responses from
136 over 8400 cells. Min and Max experimental ranges for each biomarker were computed by
137 defining a lower and upper bounds ($LB = \min(\text{mean} - 2 * SD)$ and $UB = \max(\text{mean} + 2 *$
138 $SD)$, respectively), for non-paced and paced measurements, as reported in Table 1.

139 Reference compounds were tested in 5 plates (one for each drug), considering 4 increasing
 140 doses (D1, D2, D3 and D4) and 6 multicellular samples for each dose (thus integrating
 141 responses from at least 1200 cells per drug dose). After discarding failed recordings, we used
 142 the same methods as in control to compute the experimental biomarker ranges.

143

144 **Table 1. Experimental ranges of the *in vitro* optical recordings**

	Control non-paced		Control paced	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
	(LB _{NP})	(UB _{NP})	(LB _P)	(UB _P)
AP CL (ms)	1310.2	12,798.5	---	---
ADP ₉₀ (ms)	485.1	1393.8	514.3	1397.6
APD ₅₀ (ms)	310.6	1059.6	332.5	932.4
APD ₃₀ (ms)	240.6	910.3	261.6	786.3
AP Tri ₉₀₋₃₀ (ms)	132.0	741.0	251.9	839.9
CaTr CL (ms)	1310.1	12,805.3	---	---
CTD ₉₀ (ms)	754.9	2897.5	863.2	1803.0
CTD ₅₀ (ms)	463.8	1376.4	510.5	1167.8
CTD ₃₀ (ms)	353.4	1065.2	382.7	983.7
CaTr tRise _{0,peak} (ms)	112.9	622.3	96.5	473.8
CaTr Tri ₉₀₋₃₀ (ms)	104.8	1872.5	438.6	1140.6

145 LB_{NP}: lower bound, non-paced; UB_{NP}: upper bound, non-paced; LB_P: lower bound, paced;
 146 UB_P: upper bound, paced; see main text for biomarker descriptions.

147 [Updated version of the Paci2018 hiPS-CM model](#)

148 A limitation of the Paci2018 hiPS-CM model (15) was noted - namely, failure to reproduce the
 149 cessation of the spontaneous electrical activity following strong block of the I_{NCX}, as shown by
 150 recent *in vitro* and *in silico* experiments (16, 33). A very large window current in Paci2018 for
 151 the fast Na⁺ current (I_{Na}) was identified as the key to sustaining the automaticity upon I_{NCX}
 152 block. We improved the Paci2018 model to reproduce this specific mechanism, while
 153 preserving all its good features. We kept the same structure of the Paci2018: the model includes
 154 two compartments, namely cytosol and sarcoplasmic reticulum (SR), and it follows the
 155 classical Hodgkin & Huxley formulation, which describe the membrane potential as

$$C \frac{dV}{dt} = -(I_{Na} + I_{NaL} + I_f + I_{CaL} + I_{to} + I_{Kr} + I_{Ks} + I_{K1} + I_{NCX} + I_{NaK} + I_{pCa} + I_{bNa} + I_{bCa} - I_{stim}),$$

where C is the membrane capacitance V the membrane voltage and I_{stim} the stimulus current. The ion current/pumps in the model are: I_{Na} , the late Na^+ current (I_{NaL}), the funny current (I_f) the L-type Ca^{2+} current (I_{CaL}), the transient outward K^+ current (I_{to}), the rapid and slow delayed rectifier K^+ currents (I_{Kr} and I_{Ks}), the inward rectifier K^+ current (I_{K1}), the Na^+/Ca^{2+} exchanged (I_{NCX}), the Na^+/K^+ pump (I_{NaK}) the sarcolemmal Ca^{2+} pump (I_{pCa}) and the Na^+ and Ca^{2+} background currents (I_{bNa} and I_{bCa}). The SR compartment exchanges Ca^{2+} with cytosol through three fluxes: RyR-sensitive release current (I_{rel}), SERCA pump (I_{up}) and leakage current (I_{leak}).

To develop the Paci2019 model (details in the Supporting Material):

- we updated the formulations for I_{Na} and I_f with the ones proposed in (16);
- we optimized the model parameters to fit the same dataset of *in vitro* AP and CaTr biomarkers used for (15), which have been recorded at 37°C;
- we validated the model against the same experimental protocols used for (15).

As a result, we obtained an improved version of our hiPS-CM model (Paci2019), where the spontaneous electrical activity is triggered both by I_f and Ca^{2+} release from the sarcoplasmic reticulum, which in turn depolarize the membrane potential via I_{NCX} . Details on the optimization procedure are reported in the Supporting Material, together with the model parameter values and equations.

The optically-obtained *in vitro* data in this paper were recorded at 21°C and with extracellular concentrations ($Na_o = 135.0$, $K_o = 5.4$ and $Ca_o = 1.33$ mM instead of $Na_o = 150.0$, $K_o = 5.4$ and $Ca_o = 1.8$ mM). Consequently, we implemented temperature correction of the new Paci2019 model to these conditions. Temperature difference was managed by setting the correct temperature in the specific model parameter affecting the Nernst potentials and ion currents such as I_{NCX} or I_{NaK} , rescaling the time constants of the other main ionic currents by means of the Q_{10} factors reported in (34–37), and summarized in Table S1 in the Supporting Material.

hiPS-CM *in silico* population calibrated with optical AP and CaTr recordings

The new Paci2019 model, adapted to the temperature and extracellular concentrations of the optical recordings, was used as baseline to construct a population of *in silico* hiPS-CMs, based on the population of models methodology (19, 20, 38). We sampled a total of 22 parameters in the [50-150]% range compared to their original values. Parameters were chosen similarly to (39), to include all the main ionic conductances, as well as key kinetics parameter, known to impact both AP and CaTr biomarkers: (i) the maximum conductances of I_{Na} , I_{NaL} , I_f , I_{CaL} , I_{to} , I_{Ks} , I_{Kr} , I_{K1} , I_{NCX} , I_{NaK} , I_{pCa} , I_{rel} , I_{up} ; (ii) activation and inactivation time constants of I_{Na} , I_{CaL} and I_{rel} ; (iii) adaptation time constant and half inactivation Ca^{2+} concentration of I_{rel} ; (iv) I_{up} half saturation constant. An initial population of 30,000 hiPS-CMs was generated, and then calibrated based on the optical recordings, i.e. only the models whose biomarkers were in agreement with the *in vitro* data were maintained. Biomarkers were computed in steady state (after 800s), as the average on the last 20 beats. The lack of absolute amplitude values for AP in the optically-recorded data was handled by an additional biomarker to constrain the amplitude of the non-paced AP (AP peak between 17.0 and 57.7 mV), as in (19).

198 Three different calibration options were performed considering both paced and non-paced
199 biomarkers, thus generating three different experimentally-calibrated populations: i) All AP
200 and CaTr biomarkers (AP_CaTr population); ii) AP biomarkers only (AP_only population);
201 iii) CaTr biomarkers only (CaTr_only population). The three populations were compared to
202 investigate how the choice of AP and CaTr biomarkers affect the calibration process and the
203 coverage of the biomarker space compared to experimental ranges.

204 *In silico* drug trials

205 *In silico* drug trials were performed for 5 compounds (astemizole, dofetilide, ibutilide, bepridil
206 and diltiazem) considering the 4 concentrations for each tested *in vitro*. Drug simulations were
207 run for 400s from steady state conditions. Models were not paced, to also investigate drug-
208 induced effect on the spontaneous beating frequency. We used a simple pore-block drug model
209 as in (3, 19, 38), consisting of IC₅₀ and Hill's coefficients from literature and reported in Table
210 S2 in the Supporting Material. The experimental concentrations for each drug are reported in
211 Table S3 in the Supporting Material, together with the corresponding percentage of residual
212 currents following drug application and the maximal effective free therapeutic concentration
213 (EFTPC_{max}), for comparison.

214 Because of the discrepancy between hiPSC and adult CMs observed for bepridil ((40) vs (3,
215 41)), only for bepridil 10μM, we run additional tests, reducing its I_{CaL} blocking action to half
216 (64% residual I_{CaL} instead of 32%) and to zero (100% residual I_{CaL}), while preserving its
217 blocking action on the other ion channels. This test was done on 4 models selected among the
218 ones that showed a pro-arrhythmic behaviour when administered astemizole.

219 Following drug application, we assessed the drug-induced changes on AP and CaTr
220 biomarkers, as well as the occurrence of abnormalities. Single and multiple early after-
221 depolarizations (EADs) were defined as extra-peaks greater than -55mV in between two
222 consecutive AP upstrokes. Repolarisation failure were identified when a stable ($dV/dt_{max} < 0.1$
223 V/s) membrane potential > -40 mV was observed during the last 15 s of simulation. Irregular
224 rhythm was identified when the difference in cycle length between two consecutive AP greater
225 than 150%.

226 We looked also for two additional phenotypes, that we did not consider as abnormalities:
227 quiescence (40) and residual activity (42), mainly occurring during diltiazem administration
228 (see Results). If a model reacted to drug by producing AP whose peaks were greater than -
229 40mV but smaller than 0mV, we labelled the model as residual activity. Conversely, we
230 considered the model quiescent, i.e. not producing anymore spontaneous AP, if during the last
231 15s the average membrane potential was smaller than -40mV or a potential residual activity
232 had all the peaks smaller than -40mV.

233

234 Results

235 The new Paci2019 hiPS-CMs model

236 The automated optimization process successfully identified a new Paci2019 model in
237 agreement with the *in vitro* AP and CaTr biomarkers used in (15), as shown in Table 2. Figure
238 S1 in the Supporting Material shows a detailed comparison between the new model (in black)
239 and the Paci2018 model (in red) (15). Parameter values are reported in the Supporting Material.

240 The main difference between the two models is the shape of the I_{NCX} current. Before the
241 upstroke, the new I_{NCX} provides an additional inward contribution ($-0.5A/F$) that is added to I_f
242 ($-0.25A/F$), supporting the membrane depolarization and allowing the opening of the I_{Na}
243 channels. Figure 1 illustrates the contribution of I_{NCX} to the hiPS-CM automaticity, as reported
244 in (16, 33): blocking I_{NCX} reduces its inward component slowing down the rate of spontaneous
245 AP, up to suppression. In particular, an issue in the Paci2018 model was that AP suppression
246 did not happen, in disagreement with *in vitro* data by Kim et al. (33) in response to $2\mu M$
247 SEA0400, an inhibitor of the forward I_{NCX} in a cluster of hiPS-CMs. The large I_{Na} window
248 current was identified as a key factor in supporting the automaticity, thus making the Paci2018
249 model unable to capture the aforementioned mechanism.

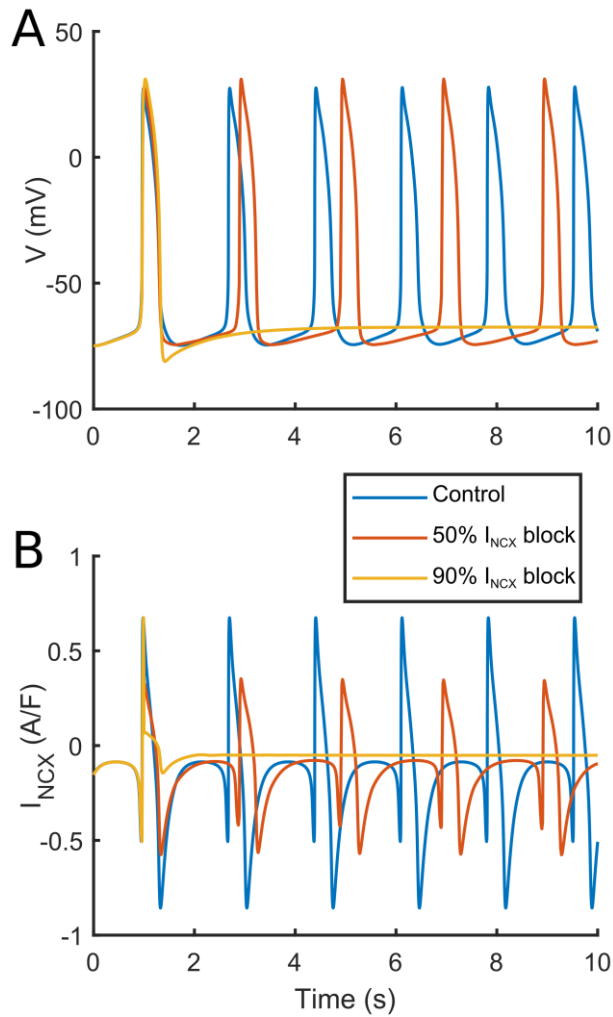
250 The new Paci2019 model can simulate spontaneous Ca^{2+} release from the SR both with
251 standard extracellular Ca^{2+} concentration ($Ca_o = 1.8mM$, Figure S2 in the Supporting Material)
252 and Ca^{2+} overload (simulated by increasing the extracellular Ca^{2+} concentration to $Ca_o = 2.8,$
253 2.9 and $3.0mM$, Figure S3 in the Supporting Material). Moreover, it reproduces well the *in*
254 *vitro* data by Ma et al. (43) with ion channel blockers (Figure S4 in the Supporting Material),
255 I_f block and hyperkalemia experiments as (33) (see Supporting Information) and alternans in
256 ischemia-like conditions as (15) (Figure S5 in the Supporting Material). Finally, the CaTr
257 amplitude of 160 nM is in agreement with data by Rast et al. (44), recorded from hiPS-CM
258 ensembles incubated at $37^\circ C$ (calibrated Fura-2-based photometry measures) and not used for
259 model calibration.

260 After updates for the extracellular ion concentrations and temperature adjustment, as described
261 in Methods, the Paci2019 model's AP and CaTr biomarkers moved closer to the optical
262 recordings reported in Table 1 obtained at room temperature. For example, spontaneous CL
263 increased (from $1,712$ to $4,144$ ms) and APD_{90} prolonged from 390 to $1,119$ ms. Figure 2 shows
264 a comparison of the Paci2019 model (green traces) vs. the same model adapted for extracellular
265 concentrations and temperature (blue traces).

266 Table 2. Action potential and Ca²⁺ transient biomarkers simulated by the Paci2019
267 hiPS-CM model at 37°C

Biomarker (reference)	Experimental value (mean±SD)	Simulated value
APA (mV) (43)	104 ± 6.0	102.0
MDP (mV) (43)	-75.6 ± 6.6	-74.9
AP CL (ms) (43)	1700.0 ± 547.7	1712.4
dV/dt _{max} (V/s) (43)	27.8 ± 26.3	20.4
APD ₁₀ (ms) (43)	74.1 ± 26.3	87.0
APD ₃₀ (ms) (43)	180 ± 58.6	223.8
APD ₉₀ (ms) (43)	414.7 ± 119.4	390.2
AP Tri (-)(43)	2.5 ± 1.1	2.8
CaTr DURATION (ms) (15)	804.5 ± 188.0	691.5
CaTr tRise _{10,50} (ms) (15)	82.9 ± 50.5	55.0
CaTr tRise _{10,90} (ms) (15)	167.3 ± 69.8	118.2
CaTr tRise _{10,peak} (ms) (15)	270.4 ± 108.3	184.0
CaTr tDecay _{90,10} (ms) (15)	409.8 ± 100.1	341.0
CaTr CL (ms) (15)	1653.9 ± 630	1712.4

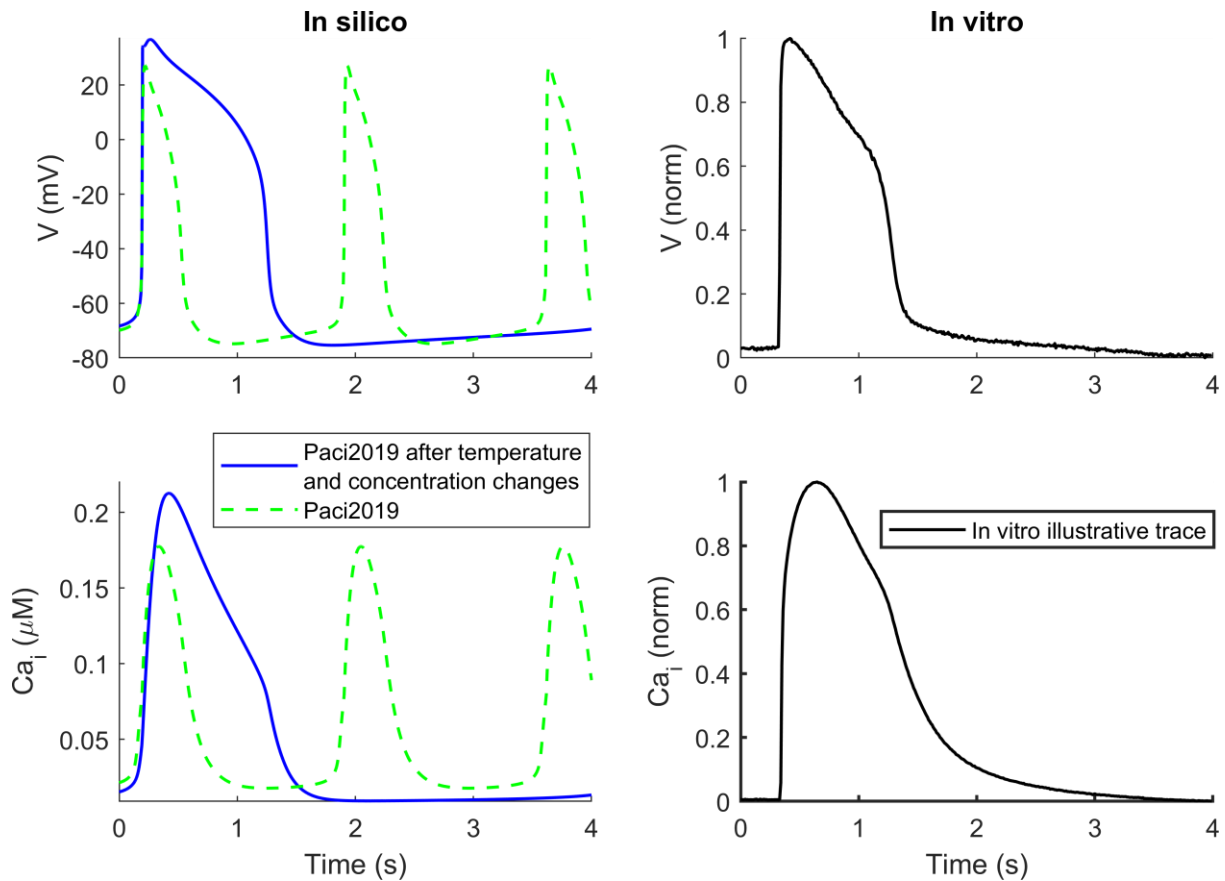
268 AP and CaTr biomarkers from (15). Both AP and CaTr biomarkers were recorded at 37°C. AP
269 biomarkers (patch-clamp): AP amplitude (APA); maximum diastolic potential (MDP); cycle
270 length (CL); maximum upstroke velocity (dV/dt_{max}); AP duration at 10%, 30% and 90% of
271 repolarization (APD₁₀, APD₃₀, APD₉₀); AP triangulation (AP Tri) computed as the ratio
272 between APD₃₀-APD₄₀ and APD₇₀-APD₈₀; CaTr DURATION; CaTr rise time from 10% to
273 50% (CaTr tRise_{10,50}), 90% (CaTr tRise_{10,90}), and to CaTr peak (CaTr tRise_{10,peak}), decay time
274 from 90% to 10% (CaTr tDecay_{90,10}), and CaTr rate (CaTr CL).



275

276 Figure 1. Effects of different levels of I_{NCX} block on the spontaneous AP simulated using the
277 Paci2019 in control (blue line), with 50% I_{NCX} block (red line), and suppressed when
278 considering high I_{NCX} block (yellow line).

279



280

281 Figure 2. Simulated spontaneous AP and CaTr for the Paci2019 model at 37°C (green) vs the
 282 same model adapted to 21°C (blue) and extracellular concentrations as in the *in vitro* optical
 283 recordings (right column, spontaneous illustrative trace).

284 [Single dataset calibration vs combined dataset calibration](#)

285 The Paci2019 model, adapted for the extracellular concentrations and room temperature used
 286 in the *in vitro* experiments, was deployed to generate an initial population of 30,000 models.
 287 As described in Methods, 3 different calibrations were performed (using AP only, CaTr only
 288 or both AP and CaTr biomarkers), leading to 3 calibrated populations: AP_only, CaTr_only
 289 and AP_CaTr, respectively.

290 A comparison of the AP and CaTr biomarkers for the 3 populations is shown in Figure 3. The
 291 AP_only population (green boxplots) consists of 969 models. As expected, it shows good
 292 agreement with the experimental AP biomarkers in addition to a good coverage of the
 293 experimental ranges, both non-paced and paced (Panel A and B). However, many models have
 294 CaTr biomarkers outside the experimental ranges, e.g. CTD₉₀, CTD₅₀ and CTD₃₀ are often too
 295 short (Panel C and D). The CaTr_only population (black boxplots) consists of 5,030 models in
 296 good agreement with CaTr biomarkers, both non-paced and paced (Panels C and D). However,
 297 many models yield AP durations and triangulation outside the experimental ranges (Panels A
 298 and B). As expected, the AP_CaTr population, obtained by calibrating with both AP and CaTr
 299 biomarkers (blue boxplots), appears to be the best constrained, with 477 models showing good
 300 agreement and coverage of the biomarker space.

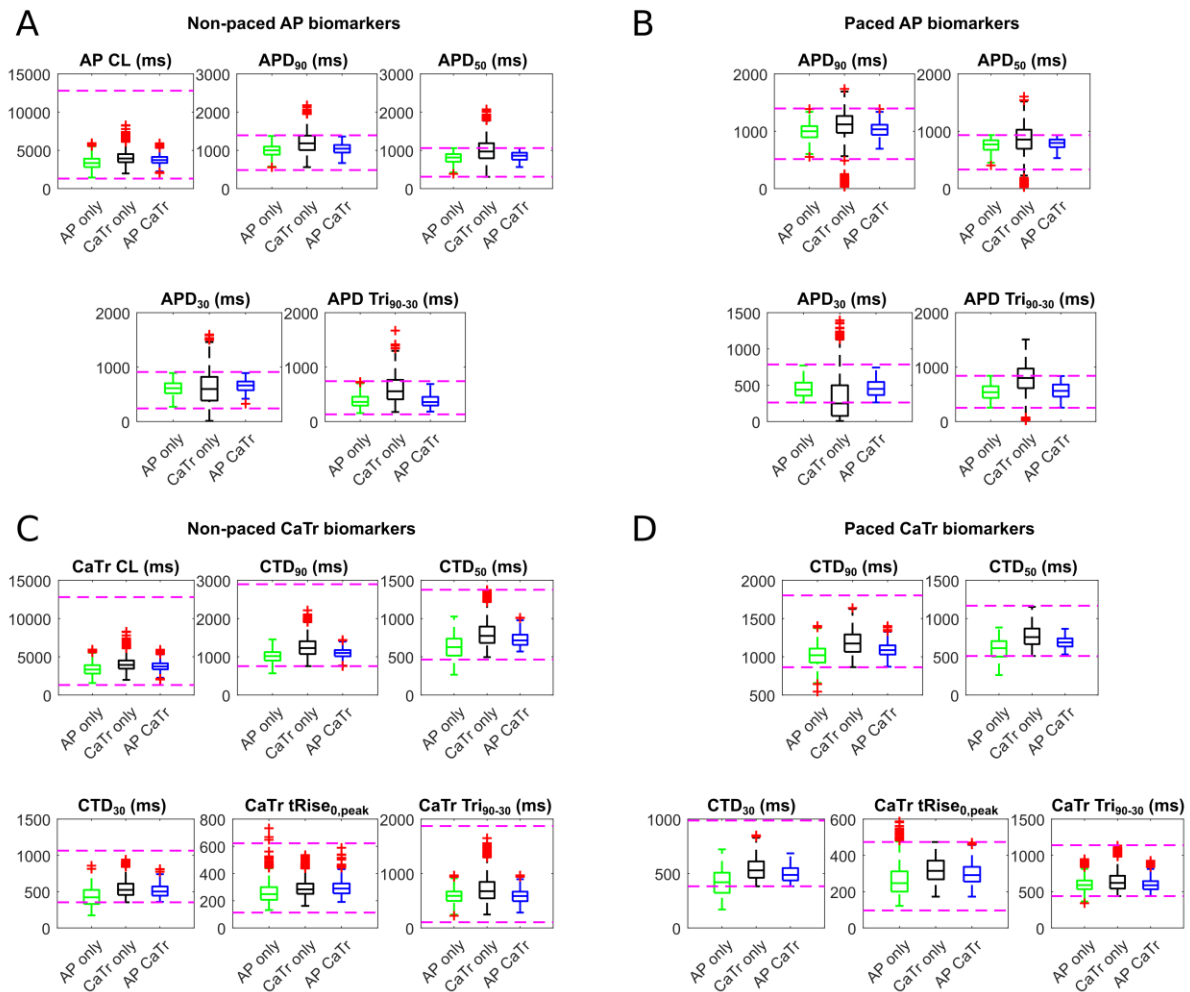
301 Figure 4 shows the distributions of the seven parameters with differential responses in the 3
 302 experimentally-calibrated populations ($|\Delta_{median}| > 10\%$ between AP_only/CaTr_only and

303 AP_CaTr). Distributions of all parameters varied in the population are shown in Figure S6 in
304 the Supporting Material. Adding AP biomarkers for calibration (AP_only and AP_CaTr
305 populations vs. CaTr_only) helps adjust five key parameters in important ways (lowers their
306 median values): G_{Na} , I_{Na} inactivation time constants, G_{K1} , I_{NCX} maximum current and I_{CaL}
307 inactivation time constant (Figure 4). The smaller G_{Na} is due to the upper limit on AP peak.
308 This also imposes a smaller I_{Na} inactivation time constant (faster inactivation), further
309 contributing to reduced AP peak amplitude. A lower G_{K1} results in a slightly depolarized MDP,
310 consequently reducing I_{Na} availability, and again limiting the AP peak. A reduced I_{NCX}
311 maximum current prevents an excessively fast early repolarization phase, e.g. short APD₃₀.
312 Finally, a smaller I_{CaL} inactivation time constant speeds up I_{CaL} inactivation, thus limiting
313 excessively long AP.

314 Considering CaTr biomarkers for calibration (CaTr_only and AP_CaTr, vs AP_only) increases
315 the median values for two calcium-release parameters: I_{rel} inactivation time constant and I_{up}
316 half saturation value (Figure 4). The first causes a slower inactivation of I_{rel} , and consequently
317 a longer CaTr (Figure 3, Panels C-D). The latter, that appears in the denominator of the I_{up}
318 formulation (15), causes a reduction of Ca^{2+} uptake, thus also contributing to a longer CaTr.

319 Overall, these results reveal important information contributed by the AP or CaTr biomarkers
320 in the calibration process to better capture the experimental recordings. For the rest of this
321 study, including the *in silico* drug trials, only the AP_CaTr population of 477 hiPS-CM
322 models was considered. The AP and CaTr traces for this population are shown in Figure 5.

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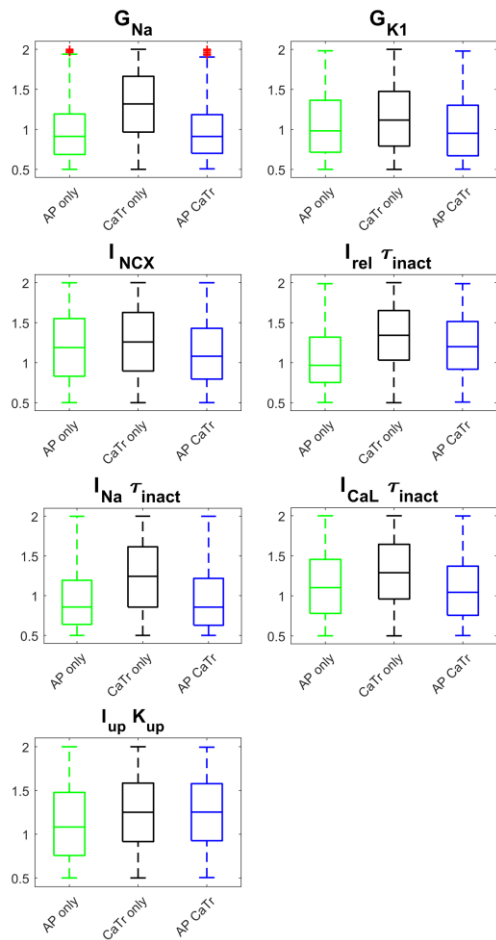


324

325 Figure 3. AP (A, B) and CaTr (C, D) biomarker distributions in the three populations of hiPS-
 326 CM models, calibrated with *in vitro* AP biomarkers only (green), CaTr biomarkers only (black)
 327 or both (blue). On each box, the central mark is the median of the population, box limits are
 328 the 25th and 75th percentiles, and whiskers extend to the most extreme data points not
 329 considered outliers. Red crosses represent outliers. The dashed magenta lines represent the
 330 lower and upper bounds of the experimental recordings, as reported in Table 1.

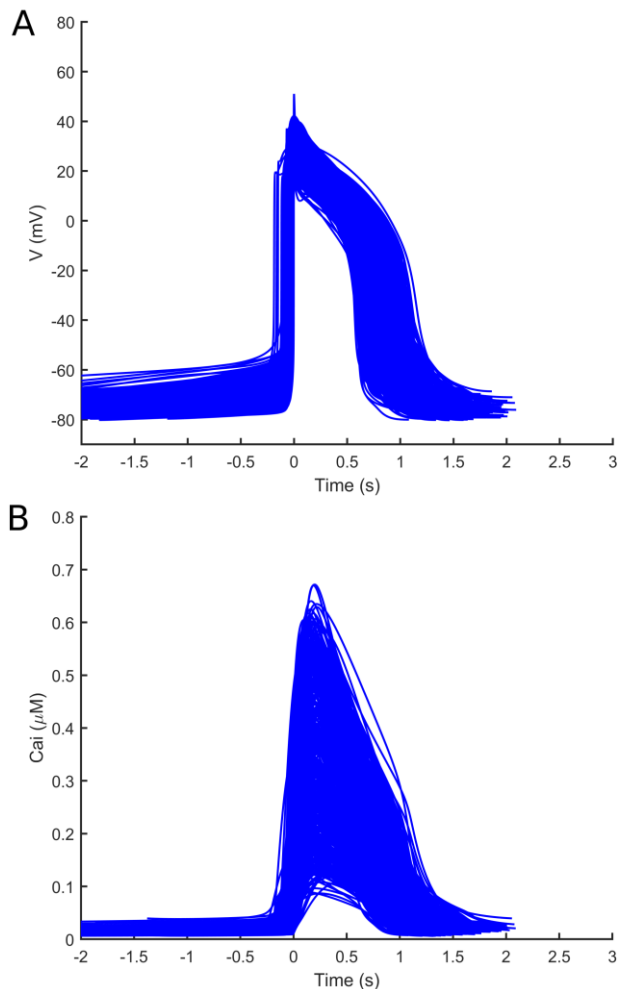
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333

334 Figure 4. Parameter distributions for the three populations: AP_only (green), CaTr_only
335 (black) and AP_CaTr (blue). Red crosses represent outliers. Boxplot description as in Figure
336 3. Only parameters with $|\Delta\text{median}| > 10\%$ between AP_only/CaTr_only and AP_CaTr are
337 shown here, while distributions of all 22 parameters are reported in Figure S6.



338

339 Figure 5. AP (A) and CaTr (B) traces included in the final population of 477 *in silico* hiPS-
340 CMs, calibrated with both AP and CaTr biomarkers.

341 *In silico* drug trials

342 Using the population of 477 hiPS-CM models shown in Figure 5, calibrated with both
343 experimental AP and CaTr biomarkers, we ran *in silico* drug trials for 5 reference compounds
344 (astemizole, dofetilide, ibutilide, bepridil, diltiazem) at 4 increasing concentrations (D1-D4)
345 each. Simulation results were validated against the corresponding *in vitro* experiments, which
346 were not used during the calibration process. For each drug trial, we checked how the drug
347 affects the AP and CaTr biomarkers compared to control (D0), and assessed the presence of
348 drug-induced abnormalities. Figure 6 summarizes the drug effects on four AP and CaTr
349 biomarkers (AP CL, APD₉₀, CTD₉₀ and CaTr Tri₉₀₋₃₀). Shown are: i) *in silico* biomarker
350 boxplots for the models that after drug administration still produce spontaneous AP and CaTr
351 at room temperature and at the ion concentrations tested *in vitro*; and ii) *in vitro* optically-
352 recorded biomarkers (green/purple diamonds) and their variability ranges (green/purple bars).
353 Results for all biomarkers are shown in the Supporting Information, Figure S7-11 in the
354 Supporting Material.

355 Our *in silico* population, calibrated with optically-recorded biomarkers in control conditions
356 only, reproduces successfully the drug-induced changes in the AP and CaTr biomarkers. If no

357 *in vitro* biomarkers are reported for a specific dose, it means that the drug stopped the
358 spontaneous activity in *in vitro* hiPS-CMs.

359 The four drugs (astemizole, dofetilide, ibutilide, bepridil), causing a strong I_{Kr} block, induced
360 AP and CaTr prolongation. In particular, simulated APDs, CaTr $t_{Rise_{0,peak}}$, and AP and CaTr
361 Tri_{90-30} are well within the experimental ranges. Conversely, simulated AP and CaTr CL and
362 CTDs tend to underestimate the prolongation observed *in vitro*. For diltiazem, a I_{CaL} blocker,
363 simulations reproduced a dose-dependent APD₉₀ shortening. However, the CTD₉₀ prolongation
364 observed *in vitro* for intermediate doses (D2 and D3) was not captured *in silico*. Table 3 reports
365 the occurrences of drug-induced repolarisation abnormalities and quiescent phenotypes, both
366 in simulations and experiments.

367 The *in vitro* dataset showed overall less abnormalities in hiPS-CMs in response to drugs than
368 the simulations. A likely reason for this could be that *in silico* results assume single-cell
369 behavior with a wide range of ionic profiles, while syncytial structures were used *in vitro*,
370 where good cell-cell coupling usually has damping effects on pro-arrhythmic behavior. For the
371 drugs inducing AP prolongation (astemizole, dofetilide, ibutilide and bepridil), the
372 abnormalities recorded *in vitro* were single or multiple early-afterdepolarizations (EADs),
373 corresponding to the types A, B and C reported in (13). We also observed 3 cases of
374 tachyarrhythmia (rate of spontaneous oscillations > 2Hz), 2 for Dofetilide (D3 and D4,
375 following EADs) and 1 for ibutilide (D4). Finally, 9 cases of irregular rhythm were observed:
376 4 for Dofetilide (D1, D2 and D3), 4 for ibutilide (D1 and D2) and 1 for Bepridil (D1). For
377 diltiazem, the abnormalities observed *in vitro* were an irregular rhythm at D1, a multiple EAD
378 and irregular rhythm at D2 and a tachyarrhythmic time course at D4 (in 6 out of 6 observations,
379 1 also with irregular rhythm).

380 In the simulations for 4 out of 5 tested compounds (astemizole, dofetilide, ibutilide and
381 bepridil) we observed a variety of drug-induced phenotypes, as seen *in vitro* both in our
382 experiments and in (13). Exemplary *in silico* traces are shown in Figure 7 and compared to *in*
383 *vitro* experiments: single and multiple EADs (panels A, B, C, D), single EADs (panel E, F),
384 repolarization failures (panels G, H) and irregular rhythms (panels I, J, K, L, M, N). Expanded
385 and additional traces are reported in Figure S12 in the Supporting Material. In addition to AP
386 shortening, for diltiazem we observed a residual electrical activity, characterized by low-
387 amplitude oscillations and an EAD (Figure S13 in the Supporting Material).

388 For astemizole, *in silico* results reveal 9 abnormalities at D3, and 43 at D4 (mainly EADs and
389 repolarization failures, but also 5 irregular rhythms per dose); the *in vitro* data show dose-
390 dependent increase in pro-arrhythmic markers but no arrhythmia events per se at the tested
391 doses. Again, the syncytial nature of the experimental samples and/or lower temperature may
392 have dampened the arrhythmia events. Nevertheless, the simulation results are in agreement
393 with the fact that at clinical doses, this drug is considered as intermediate risk in (40) on hiPS-
394 CMs and at high risk in the *in silico* drug trials performed in (3) and in CredibleMeds (41).
395 This highlights the value of *in silico* investigations with broader population of models to
396 complement *in vitro* experiments, and ability to cover a wide range of ionic profiles.

397 Simulations of ibutilide and dofetilide closely agree with the experiments. A dose-dependent
398 increase in abnormalities was seen, typical of drugs classified as high risk in CredibleMeds
399 (41) and in hiPS-CMs in (40). The abnormalities *in silico* are mainly EAD and repolarization
400 failures at the higher doses, together with few cases of irregular rhythm (ibutilide: 1 at D3 and
401 2 at D4; dofetilide: 1 at D1, 5 at D2, 6 at D3). For dofetilide, at D4 we observed *in silico* only

402 5 repolarization abnormalities and 9 irregular rhythms, while all 6 *in vitro* recordings showed
403 single or multiple early EADs. Therefore, we tested *in silico* 3 additional doses higher than D4,
404 as in (3), that triggered a considerable amount of EADs (up to 59 EADs/repolarization failures
405 at D7).

406 Bepridil simulations are in agreement with our *in vitro* experiments. Bepridil's main effect on
407 hiPS-CMs is the suppression of spontaneous activity in a high percentage of the population
408 (107/477 and 444/477 models, at D3 and D4, respectively). This is consistent with our *in vitro*
409 experiments (6/6 observations at D4 did not produce AP) and with other reports (40).
410 Conversely, only few abnormalities were observed in hiPS-CMs: *in vitro* only 1 irregular
411 rhythm at D1 and *in silico* 5 and 6 abnormalities (2 irregular rhythms and the rest EADs) for
412 D3 and D4, respectively, in agreement also with (40). However, this is in contrast with the high
413 bepridil toxicity observed for adult cells *in vitro* and *in silico*, where it triggers many
414 repolarization abnormalities (3, 41) and might be due to the different expression of ion currents
415 in adult and hiPS-CMs, especially I_{CaL} (13). Therefore, for bepridil only, we tested also the
416 effect of modulating its I_{CaL} blocking power, not changing the drug effect on I_{Na} , I_{Kr} and I_{NaL} .
417 Figure 8 shows four different models that developed abnormalities with astemizole D4, but not
418 with Bepridil D4 (black traces). However, reducing to half bepridil I_{CaL} blocking power was
419 already enough to trigger EADs. The same behavior was observed by fully inhibiting bepridil
420 I_{CaL} blocking effect.

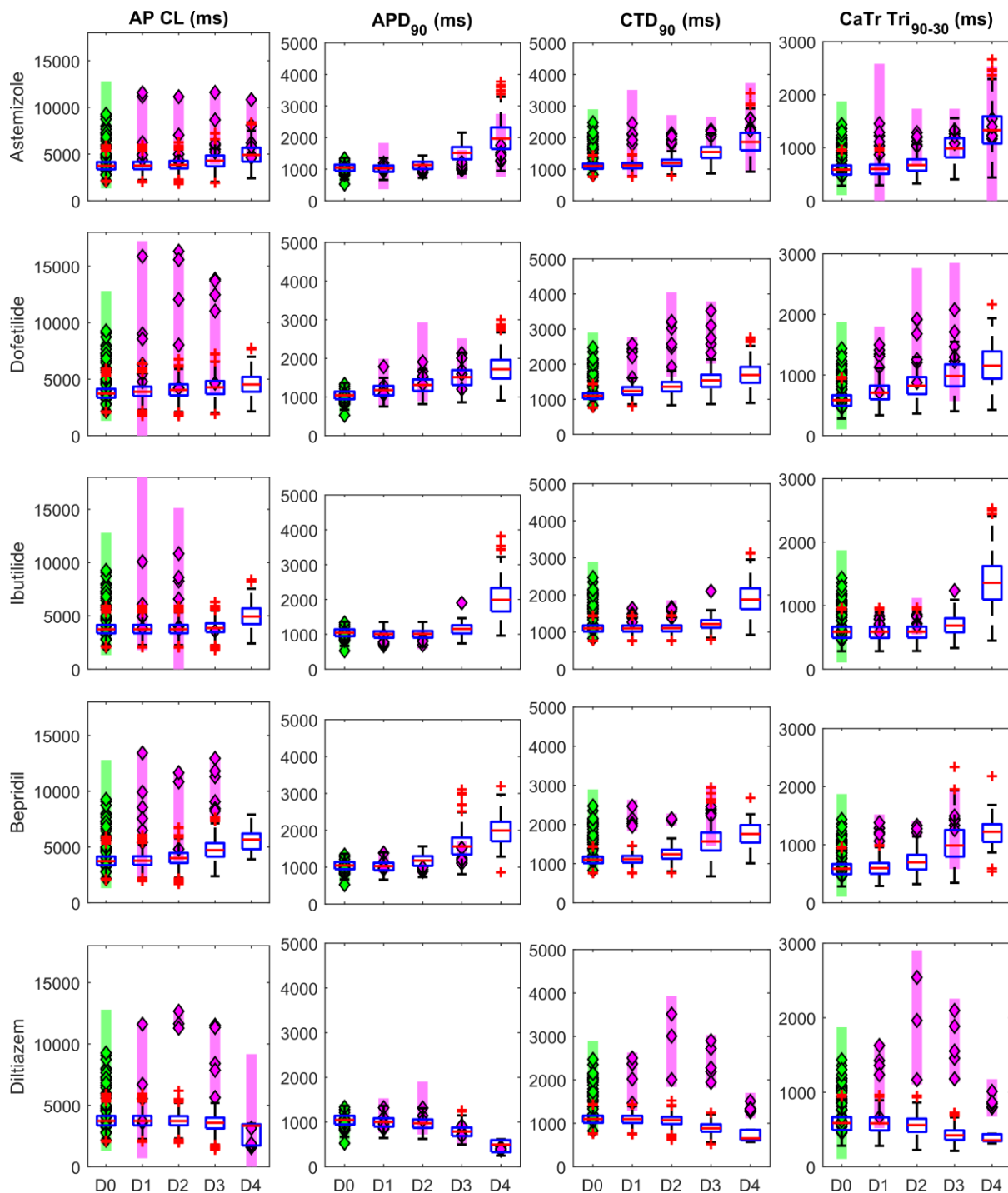
421 For diltiazem, we observed *in silico* only 1 EAD at D4 (Figure S13, Panels C), but no
422 tachyarrhythmic rhythm, as in our *in vitro* experiments. In fact, most of our models (Table 3)
423 stopped their spontaneous AP, in agreement with what was observed in (40). However, 20
424 models at D4 showed a strong decrease in AP amplitude (in few cases peaks were recorded
425 below 0mV) and slight increase of frequency (Figure S13, Panels A and B). This low-amplitude
426 oscillations (or residual activity) of the membrane potential were observed in Zeng et al. (42).
427 Zeng et al. demonstrated that such residual electrical activity is due to a residual availability of
428 I_{Na} , not fully blocked by drugs specifically designed to mainly block L-type Ca^{2+} channels. It
429 is possible that such abnormal re-activation of I_{Na} may have triggered re-entrant (tachycardic)
430 responses in our multicellular experiments. *In silico* results provide further insights that this
431 residual spontaneous electrical activity is due to a combination of residual I_{Na} (partly blocked
432 by diltiazem, but still able to trigger an AP), strong I_f and weak I_{K1} (Table S4 in the Supporting
433 Material, column RESAC).

434 Simulation studies were used to better understand biophysical mechanisms underlying the
435 drug-induced phenotypes. We observed that the abnormalities induced by astemizole,
436 dofetilide and ibutilide are mainly repolarization abnormalities, while bepridil and diltiazem
437 mainly stopped the spontaneous activity. Table S4 summarizes the ionic parameter differences,
438 the amount of repolarization abnormalities and residual activity at the maximal dose tested *in*
439 *in silico* (D4, except D7 for dofetilide). For the cessation of the spontaneous activity, D3 had more
440 balanced groups for bepridil and diltiazem. We focused our analysis only on those groups
441 containing at least 20 models showing non-sinus rhythm. Models developing EADs and
442 repolarization failures in response to astemizole, dofetilide and ibutilide show weak I_{Ks} and I_{K1}
443 compared to the models not developing such abnormalities, highlighting a reduced
444 repolarization reserve. Also I_{pCa} , an outward flow of Ca^{2+} ions is very small, contributing to
445 accumulation of positive charges in the cytosol. Conversely, a different pattern emerged for the
446 models that terminated their spontaneous activity in response to bepridil and diltiazem. They

447 show, compared to the models still developing AP at D3, a strong I_{K1} that stabilizes the resting
448 potential. Furthermore, especially for bepridil, the stronger I_{up} half saturation constant K_{up}
449 reduces the intake of Ca^{2+} by the SERCA pump and therefore the Ca^{2+} available to be released
450 from the sarcoplasmic reticulum, impairing the Ca^{2+} handling that it is now an important
451 component of automaticity in the Paci2019 model. For diltiazem, we found that I_{Na} was smaller
452 in models where the drug terminated spontaneous activity compared to the group that still
453 showed spontaneous activity.

454

455



456

457 Figure 6. Summary of the drug-induced changes on 4 non-paced AP and CaTr biomarkers in
 458 the *in silico* population of hiPS-CMs vs *in vitro* optical recordings. Each line shows results for
 459 a different drug, tested at 4 concentrations (D1-D4) and compared to control conditions (D0).
 460 Each column corresponds to a different biomarker. In each panel: blue boxplots, simulated
 461 biomarkers (Boxplot description as in Figure 3); green diamonds, *in vitro* control biomarkers;
 462 purple diamonds, *in vitro* biomarkers following drug applications; green/purple bars,
 463 experimental ranges of the *in vitro* data. If no *in vitro* biomarkers are reported for a specific
 464 dose, it means that it was not possible computing the biomarkers on the AP and CaTr.

465

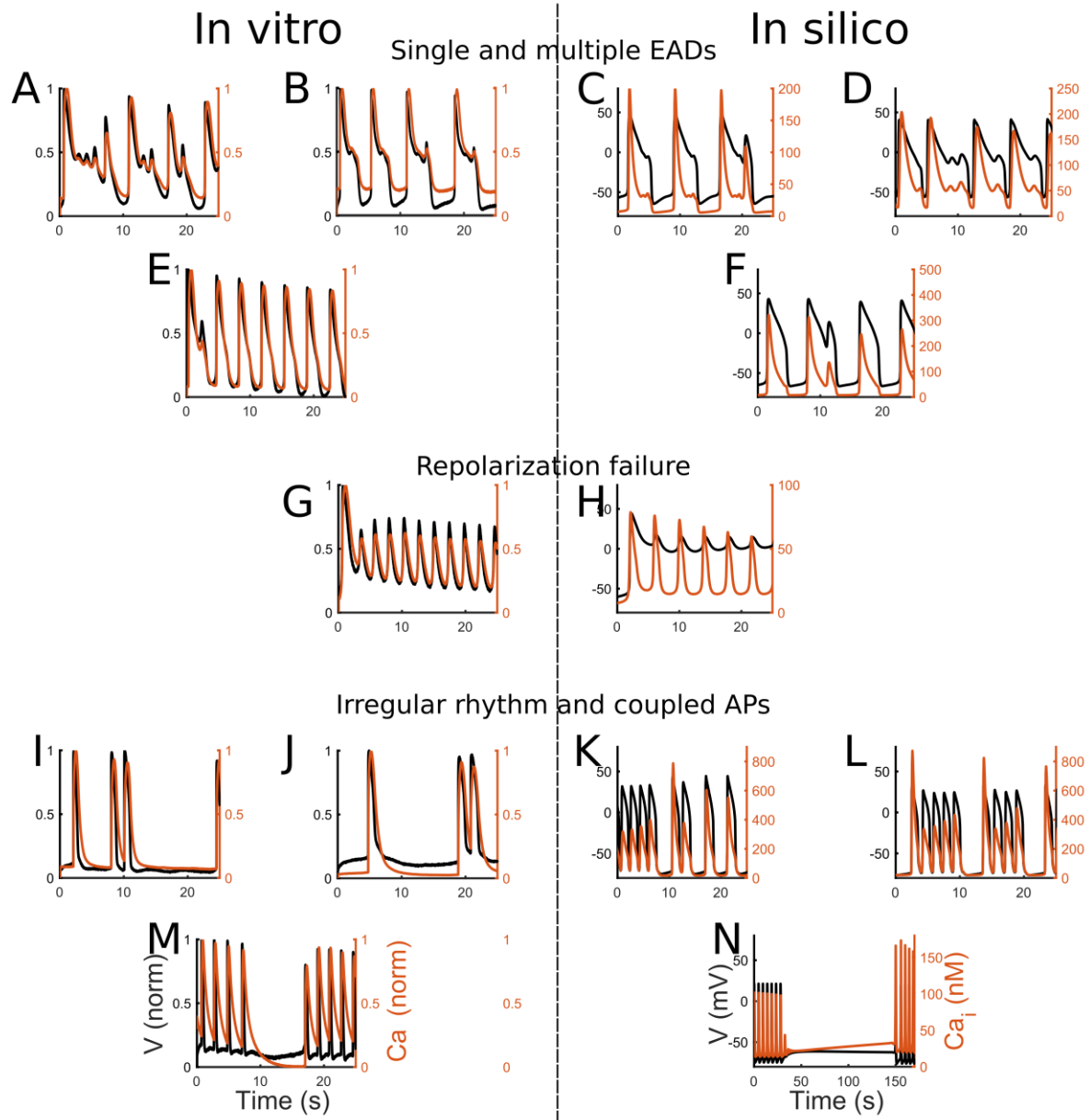
466 Table 3. Drug-induced abnormalities observed in *in silico* vs *in vitro* non-paced hiPS-CMs.

Drug	Dose	<i>In silico</i>					<i>In vitro</i>					
		OK	Q	RA	IRR	RESAC	OK	Q	RA	IRR	RESAC	Tachy
Astemizole	D1	476	1	-	-	-	6	-	-	-	-	-
	D2	475	2	-	-	-	6	-	-	-	-	-
	D3	466	2	4	5	-	6	-	-	-	-	-
	D4	432	2	38	5	-	6	-	-	-	-	-
Bepridil	D1	472	5	-	-	-	5	-	-	1	-	-
	D2	466	11	-	-	-	6	-	-	-	-	-
	D3	365	107	3	2	-	6	-	-	-	-	-
	D4	27	444	6	-	-	-	6	-	-	-	-
Diltiazem	D1	477	-	-	-	-	5	-	-	1	-	-
	D2	452	25	-	-	-	4	-	1	1	-	-
	D3	204	269	-	4	-	6	-	-	-	-	-
	D4	12	444	1	-	20	-	-	-	1*	-	6*
Dofetilide	D1	474	2	-	1	-	4	-	-	2	-	-
	D2	470	2	-	5	-	5	-	-	1	-	-
	D3	466	2	3	6	-	5	-	-	1	-	-
	D4	461	3	4	9	-	-	-	6*	-	-	2*
	D5	455	3	12	7	-	-	-	-	-	-	-
	D6	435	1	39	2	-	-	-	-	-	-	-
	D7	414	1	59	3	-	-	-	-	-	-	-
Ibutilide	D1	477	-	-	-	-	5	-	-	1	-	-
	D2	477	-	-	-	-	3	-	-	3	-	-
	D3	474	2	-	1	-	-	-	6	-	-	-
	D4	427	1	47	2	-	-	-	5	-	-	1

467

468 OK: spontaneous beating with no abnormalities; Q: quiescence; RA: repolarization
 469 abnormalities (early afterdepolarizations and/or repolarization failure); IRR: irregular rhythm;
 470 RESAC: residual activity; Tachy: tachyarrhythmic oscillations; '-': phenotype not observed;
 471 *: *in vitro* observations showed more than one abnormal phenotype. For dofetilide,
 472 D5=10xEFTPC_{max}, D6=30xEFTPC_{max} and D7=100xEFTPC_{max} were tested only *in silico*, to
 473 assess if doses higher than D4 would have triggered more abnormalities.

474



475

476 Figure 7. Illustrative abnormalities observed at room temperature during the drug trials *in vitro*
 477 (left column) and *in silico* on the population from Figure 5. AP (black) and CaTr (orange). (A,
 478 B, C, D) Single and multiple EADs. (E, F) Single EADs. (G, H) Repolarization failure. (I, J,
 479 K, L) Irregular rhythms and coupled APs. (M, N) Irregular rhythm, temporary cessation of the
 480 spontaneous activity.

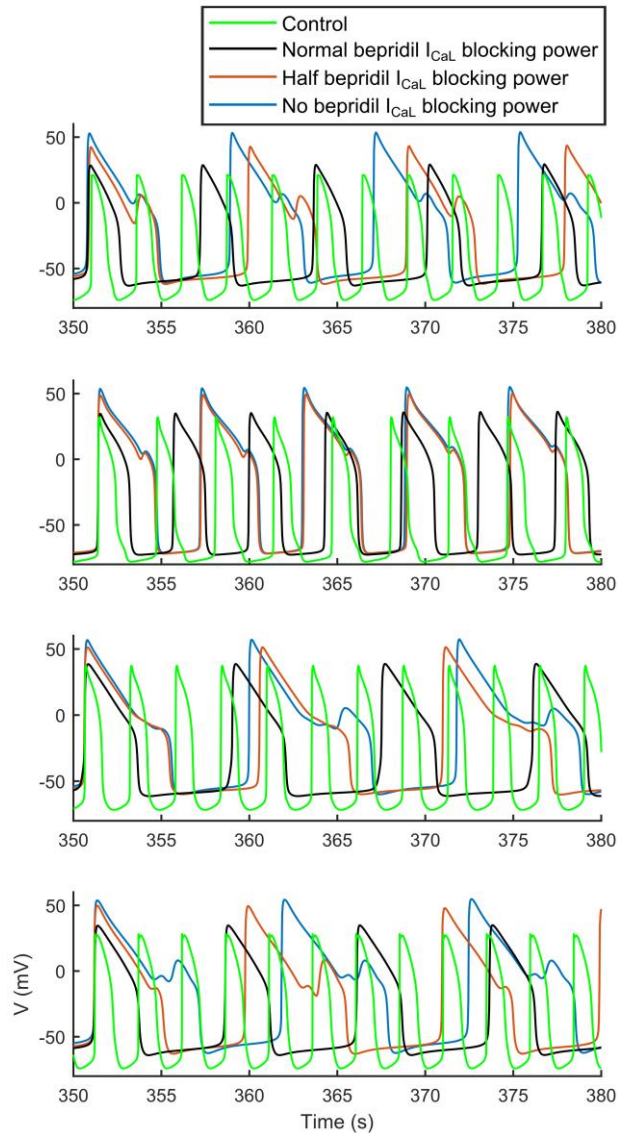
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487 Figure 8. Effect of different I_{CaL} block level during administration of D4 Bepridil. For each of
488 the 4 models (whose control AP are reported in green), we reduced bepridil blocking action of
489 I_{CaL} : normal I_{CaL} block (68% block in black); 36% I_{CaL} block (in orange); no I_{CaL} block (in
490 blue). Bepridil effect on the other ion currents was not changed. Drug trials were performed at
491 room temperature.

492

493 Discussion

494 Here we demonstrate the integration of human *in silico* drug trials and optically-recorded
495 simultaneous AP and CaTr data from hiPS-CMs for prediction and mechanistic investigations
496 of drug action. We report:

- 497 • An improved version of the Paci2018 hiPS-CM model (15) was developed and
498 validated. It better reflects the mechanisms underlying AP automaticity.

- 499 • The value of comprehensive high-throughput optical measurements of cellular
500 responses, especially combining AP and CaTr, is demonstrated in refining *in silico*
501 populations of models.
- 502 • The predictive power of the experimentally-calibrated population of hiPS-CMs models
503 is demonstrated through *in silico* drug trials on 5 drugs and comparison to *in vitro*
504 datasets.
- 505 • Mechanistic insights are gleaned from *in silico* population runs to understand
506 differential responses of hiPS-CM and adult cardiomyocytes to bepridil. Despite
507 observed cardiotoxicity in adult cells (3, 41), *in vitro* experiments, in this dataset as well
508 as in another independent *in vitro* dataset (40), showed low occurrence of proarrhythmic
509 markers in hiPS-CMs. *In silico* trials with the hiPS-CMs models show a wide range of
510 responses to drug action, which complement and explain the *in vitro* experiments.

511 Research on hiPS-CMs is rapidly developing, with new experimental data becoming available,
512 which in turn serve as a driving force for the constantly evolving computational models to offer
513 more accurate *in silico* tools to the scientific community. Based on *in vitro* (33) and *in silico*
514 (16) tests, it was identified that our Paci2018 hiPS-CM model (15) did not properly reflect the
515 role of *INCX* in automaticity, i.e. no cessation of spontaneous activity was seen in the model as
516 consequence of a strong *INCX* block, as suggested by experiments. Therefore, we updated this
517 hiPS-CM model to reproduce the specific mechanisms reported in (16, 33). (Figures 1, S1 and
518 Supporting Material). In addition, the new Paci2019 model also qualitatively simulates the
519 relationship between changes in CL and APD₉₀ as consequence of the *I_f* modulation (Figure
520 S16 in the Supporting Material). The model responds to *I_f* augmentation with shorter CL and
521 APD₉₀, while *I_f* reduction increases them. In Rast et al. (45), a similar relationship was
522 observed in iCells (CDI) hiPS-CMs field potentials between the inter-beat interval and the field
523 potential duration for ivabradine (for *I_f* reduction) and forskolin (for *I_f* augmentation).

524 Using the Paci2019 model to construct an *in silico* population based on our *in vitro* optical
525 recordings, we showed that the combination of AP and CaTr biomarkers provides superior
526 calibration, with a better coverage of the biomarker space (Figures 3). It is also interesting that
527 the calibration with AP biomarkers was the most restrictive: AP_CaTr and the AP_only
528 populations contained only 477 and 968 accepted models, respectively, while the CaTr_only
529 population contained over 5,000, many of which were inadequate, e.g. presented extremely
530 short or long APs (Figure S14 in the Supporting Material). Therefore, model calibration
531 exclusively based on CaTr can easily lead to inclusion of more unrealistic models for hiPS-
532 CM. For this cell type, AP biomarkers are preferred to obtain physiological (or semi-
533 physiological) models, while combining both biomarkers clearly refines the calibration. These
534 tests highlight the importance of the calibration process and one of the main advantages of
535 comprehensive records, such as the ones obtained through all-optical cardiac electrophysiology
536 systems like OptoDyCE, that allow the acquisition of AP and CaTr in large populations of cells
537 in their multicellular context.

538 Figures 6 and S7-11 compare simulated and experimental biomarkers. Of note, the
539 experimental drug trials were not used to calibrate the population of models; yet, the
540 experimentally observed biomarker trends over increasing drug doses, in particular APDs,
541 CTDs and Tri₉₀₋₃₀, were successfully reproduced. Moreover, for CaTr tRise_{0,peak} and AP and
542 CaTr Tri₉₀₋₃₀, simulations showed good reproduction of the experimental variability intervals.
543 CTDs were generally underestimated at the various drug doses. A possible reason for this is

544 the fact that in the control population (Figure 3) CTDs are included in the variability ranges,
545 but they cannot cover the higher values. Physiologically-correct *in silico* drug-induced CaTr
546 prolongation (except for diltiazem) was seen, as proven by the overlapping of the *in silico* and
547 *in vitro* CaTr Tri₉₀₋₃₀. However, the CTD₉₀ and CTD₃₀ absolute values after drug administration
548 were overall smaller *in silico* than *in vitro*.

549 We were able to obtain the same abnormality classes (Figure 7) observed in our *in vitro* data
550 and in (13), i.e. single and multiple EADs (panels A, B, C, D, E, F), with the addition of
551 repolarization failure (panels G and H), and irregular rhythms (panels I, J, K, L, M, N).
552 Conversely, the *in silico* models did not show tachyarrhythmias observed e.g. in (13) or in 6
553 cases in our *in vitro* experiments in response to the highest dose of diltiazem. As discussed
554 previously, these tachyarrhythmias may be syncytium-level events *in vitro* that could not have
555 been captured in the simulations. Furthermore, a common response of the *in silico* hiPS-CMs,
556 especially to administration of diltiazem and bepridil, is the suppression of spontaneous
557 activity. Indeed, diltiazem administration at D3 and D4 also stopped the spontaneous AP in a
558 big portion of our *in silico* population, 269 and 444 models out of 477, respectively. This is in
559 agreement with the *in vitro* diltiazem experiments of 7 out of 15 laboratories involved in the
560 multisite study reported in (40), where 100% of the hiPS-CMs tested did not produce
561 spontaneous AP after administration of 10 μ M diltiazem (equals to our D4). Furthermore, in 5
562 laboratories a variable amount (20% - 70%) hiPS-CMs stopped beating. The same effect was
563 observed for bepridil. In fact, as consequence of D3 and D4 bepridil administration, 107 and
564 444 models out of 477 stopped. Again, this is in agreement with our *in vitro* experiments (no
565 spontaneous AP at D4), and with the experiments of (40) (50% hiPS-CMs stopped spontaneous
566 AP in 4 laboratories (out of 15) with D3 bepridil, and over 80-90% hiPS-CMs in 15 laboratories
567 with D4 bepridil).

568 It is interesting to note that in our *in vitro* experiments, despite the reliable AP and CaTr
569 duration and triangulation increase, astemizole did not induce abnormalities, while they were
570 observable in 9 *in silico* hiPS-CMs at D3 and 43 at D4. Astemizole is considered an
571 intermediate risk drug in (40) and a high-risk drug both *in vitro* (46) and in the *in silico* drug
572 trials performed in (3). Especially in Blinova et al. (40), 11/15 laboratories observed single
573 and multiple EADs in 100% of their cells at 37°C, in response to 0.1 μ M astemizole (equivalent
574 to our D4). The absence of EADs in our *in vitro* data (while showing pro-arrhythmic markers
575 such as APD prolongation and increased APD triangulation), may be due to a number of
576 reasons. One possibility is the lower temperature, though temperature-corrected *in silico* hiPS-
577 CMs revealed repolarization abnormalities. Another reason could be potentially higher I_{K1} (and
578 or I_{Ks}) in our high-density syncytial preparations compared to other studies.

579 Overall, hiPS-CMs proved to be an effective *in vitro* and *in silico* model to test drug-induced
580 adverse cardiac effects. Unexpected results *in vitro* and *in silico* for bepridil, considered a
581 highly cardiotoxic drug (3, 41), prompted further investigation. As reported in Table 3, bepridil
582 triggered a very small amount of abnormalities in our *in silico* population. This is in agreement
583 with our *in vitro* experiments and with the tests performed by Blinova et al. (40): in this
584 multisite study, used here for comparison only, bepridil stopped the spontaneous AP in 80-90%
585 hiPS-CMs in all the 15 laboratories at the highest bepridil dose 10 μ M (in agreement with our
586 simulations); abnormalities were seen only in 2 out of 15 laboratories. Potential reason for this
587 discrepancy can be the higher expression of L-type Ca²⁺ channels observed *in vitro* in hiPS-
588 CMs than in adult cells (13). Blinova et al. (40) state: "Bepridil is a potent hERG blocker that

589 also blocks L-type calcium and peak and late sodium currents at higher concentrations. High
590 expression levels of calcium ion channels in hiPSC-CMs as compared to primary ventricular
591 tissue may have contributed to more attenuated cellular proarrhythmic effects of the drug as
592 compared to other drugs in the high TdP risk category." We were able to test this idea *in silico*:
593 Figure S15A in the Supporting Material shows I_{CaL} in the original O'Hara-Rudy model of
594 human adult ventricular cell (34) (black trace) and in our hiPSC-CM *in silico* population
595 translated to 37°C (cyan traces). We tested if high levels of I_{CaL} could have had a pseudo-
596 protective effect against bepridil in hiPSC-CMs, partially compensating the I_{Kr} block, resulting
597 in a milder effect than in cells expressing less I_{CaL} (e.g. adult cardiomyocytes). At room
598 temperature, we tested bepridil D4 on 4 *in silico* hiPSC-CMs that showed abnormalities with
599 astemizole, by reducing bepridil I_{CaL} blocking power first to half of its original value and then
600 completely. This resulted in abnormalities in all 4 models (Figure 8), as expected. In addition,
601 these 4 models in control conditions and 37°C showed I_{CaL} higher than the adult one (Figure
602 S15B). Table S2 shows the IC_{50} used for our *in silico* drug trials, taken from (3). Bepridil has
603 the closest I_{Kr} and I_{CaL} IC_{50} among APD-prolonging drugs. Therefore, an I_{CaL} block comparable
604 to I_{Kr} block in condition of highly expressed I_{CaL} could indeed compensate APD prolongation
605 and mask the occurrence of abnormalities, which may have occurred in adult cardiomyocytes
606 (as reported *in silico* in (3, 47)). Our *in vitro* and *in silico* tests show the undeniable value of
607 hiPSC-CMs as models for drug testing and how *in silico* simulations could benefit the
608 interpretation of the *in vitro* tests. The hiPSC-CMs represent a potentially infinite pool of human
609 cardiomyocytes and can capture key aspects of human cardiac electrophysiology in normal and
610 diseased conditions (genetic mutations). Therefore, they are a great asset to predict the
611 occurrence of adverse drug effects, in a unparallel manner that can be patient-specific.

612 As all experimental models, the hiPSC-CMs are not without limitations. For example, they have
613 different ion current expressions than adult cardiomyocytes, potentially affecting I_{Na} , I_{CaL} , I_{Kr}
614 and I_{Ks} (see Figure 2 in (13)), i.e. currents for which IC_{50} values are commonly computed. It
615 must be noted that extensive experimental datasets from healthy adult human cardiomyocytes
616 are non-existent due to unavailability of such cardiac tissue. Thus, inferences could only be
617 made based on donor heart-derived human cells (34, 47, 48) or well-studied adult
618 cardiomyocytes from other species. Nevertheless, different ion channel expressions can lead to
619 underestimation (as for bepridil) or overestimation of the actual toxicity of a drug. A variety of
620 optimization approaches are being developed to improve the maturity of the hiPSC-CMs and
621 bring them closer to an adult phenotype. These include extracellular matrix optimizations,
622 stimulation protocols, mass transport improvements, alignment, substrate and metabolic
623 function optimizations etc. (49). Such advances can impact positively cardiotoxicity testing.

624 Overall, commercial hiPSC-CMs (e.g. CDI) have demonstrated their utility and superiority to
625 animal models, even in their current state of maturity. Here we show the suitability of optically-
626 recorded data from hiPSC-CMs to produce information that empowers *in silico* modelling. With
627 suitably-high acquisition rates, optical data can provide accurate temporal biomarkers for *in*
628 *silico* models. All available Ca^{2+} data is indeed obtained by optical means; with the
629 development of new small-molecule and genetically-encoded voltage dyes, AP records may
630 completely replace electrical measurements due to their contact-less nature, easy parallelization
631 and ability to measure cell properties in multicellular context. However, absolute values remain
632 a challenge for optical measurements as voltage and Ca^{2+} -sensitive dyes are rarely calibrated,
633 i.e. they cannot provide reliable amplitude information for AP or CaTr, i.e. mV or mM. Such

634 absolute values were essential in (19) to calibrate our first hiPS-CM population; in fact, AP
635 peak <57.7mV (19) was included as a biomarker here to avoid unrealistic membrane potentials.

636 During our *in silico* tests, three limitations emerged. Firstly, CTD₉₀, CTD₅₀ and CTD₃₀ are
637 underestimated during drug administration (Figure 6, rows 1-4). The reason is that the 477
638 models in the population show relatively short control CaTr despite correct inclusion in the
639 variability ranges by calibration. While the *in silico* CaTr correctly captured the drug-induced
640 trends, they underestimated the changes observed experimentally. The *in silico* CaTr Tri₉₀₋₃₀
641 matched well the experimental values, i.e. CaTr triangulation during drug administration was
642 captured. In case of diltiazem (Figure 6, last row) we observed a peculiar behavior of the *in*
643 *vitro* measurements following drug administration, since the CaTr showed larger CTDs at D2
644 and D3 than at D1, in spite CTD₉₀ shortening for increasing diltiazem doses is clear from D2
645 to D4. The second limitation is that up to D4 *in silico* dofetilide generated few abnormalities,
646 while D4 dofetilide triggered *in vitro* EADs in all the measurements. We observed already in
647 (22) that to induce a remarkable amount of EADs or repolarization failures in an *in silico* hiPS-
648 CM population, we needed I_{Kr} block>90%. Conversely, D4 dofetilide blocks only 80% I_{Kr}.
649 With higher doses, tested in (3), we obtained a considerable increase in AP abnormalities.
650 Finally, we did not observe in our simulations tachyarrhythmias as seen *in vitro* in a few
651 samples, perhaps due to difference in single vs. multicellular behavior. We observed higher
652 spontaneous AP rates, e.g. in irregular rhythms (e.g. in Figure S12, panel I, AP rate goes to
653 0.59Hz or a cycle of 1700ms) or residual activity in case of diltiazem (in Figure S13, Panel B,
654 rate up to 0.83Hz, corresponding to AP CL of 1200ms). However, we did not observe AP rates
655 greater than 2Hz.

656 Conclusions

657 In conclusion, this work supports the use of high-content, high-quality all-optical
658 electrophysiology data to develop, calibrate and validate computer models of hiPS-CM for *in*
659 *silico* drug trials. We report that simultaneously-acquired AP and CaTr enhance the model
660 calibration process to obtain a final population that better reflects the experimental recordings.
661 Our population was able to reproduce the effect of 5 different compounds, including the drug-
662 induced abnormalities observed *in vitro*. *In silico* models constrained by *in vitro* data can be
663 used to expand the parameter space of the investigations and to glean mechanistic insights into
664 drug action. Finally, our simulations highlight the importance of being aware and taking into
665 account potential differences in ionic currents between hiPS-CMs and adult cardiomyocytes,
666 which could result in differences between *in vitro/in silico* hiPS-CMs and *in vivo* outcomes for
667 specific compounds.

668 Author Contributions

669 AK and EE recorded and analyzed the optical *in vitro* data. MP and SS designed the Paci2019
670 hiPS-CM model. MP, EP, SS, JH, BR and EE designed the *in silico* tests on the populations of
671 models. MP implemented the models and software tools used to produce and analyze the *in*
672 *silico* data. MP, EP and SS analyzed the *in silico* data. All authors contributed to the writing
673 and reviewed the manuscript.

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687 Supporting Citations

688 References (50-55) appear in the Supporting Material.

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