

1 Step by step, cell by cell: quantification of the bacterial
2 cell cycle

3 Matteo Osella^a, Sander J. Tans^b, Marco Cosentino Lagomarsino^{f,c,d,e}

4 ^a*Dipartimento di Fisica and INFN, University of Torino, V. Pietro Giuria 1, Torino,*
5 *I-10125, Italy*

6 ^b*FOM Institute AMOLF, Science Park 104 1098 XG Amsterdam, The Netherlands*

7 ^c*Sorbonne Universités, Université Pierre et Marie Curie, UMR 7238, Institut de*
8 *Biologie Paris Seine, 4, Place Jussieu, 75005 Paris, France*

9 ^d*CNRS, UMR 7238 Computational and Quantitative Biology, Paris, France*

10 ^e*FIRC Institute of Molecular Oncology (IFOM), 20139 Milan, Italy*

11 ^f*Correspondence: marco.cosentino-lagomarsino@upmc.fr*

12 **Abstract**

13 The *Escherichia coli* cell cycle is a classic, but we are still missing some
14 of its essential aspects. The reason is that our knowledge is mostly based on
15 population data, and our grasp of the behavior of single cells is still very lim-
16 ited. Today, new dynamic single-cell data promise to overcome this barrier.
17 Existing data from single cells has already led to findings and hypotheses
18 that challenge standard views, and raised new questions. Here, we review
19 these recent developments and propose that a systematic exploration of the
20 correlation patterns between “cell cycle intervals” defined by key molecular
21 events measured in many single cells could lead to a quantitative character-
22 ization of the cell cycle in terms of inherent stochasticity and homeostatic
23 controls.

24 *Keywords:* Cell-cycle, Division Homeostasis, E. coli, Stochasticity, Key
25 intervals, Replication initiation

26 **1. The cell cycle is a feature of single cells.**

27 Based on all the research on the cell cycle of *E. coli*, We might think that
28 we know a great deal about this problem. And to some extent, this is true.
29 The discovery of a key role of **replication initiation** (see Glossary) dates
30 back to work from the late 1960s [1, 2], and by the early 1990s most of the
31 molecular players that we consider relevant today had been identified [3].

32 However, it is not difficult to convince ourselves that we are missing some
33 essential aspects of the problem. The reason is that most of the information
34 in our possession comes from bulk **population measurements** and indirect
35 inference. In this Opinion piece, we argue that today it is the right moment to
36 revisit the *E. coli* cell cycle exploiting dynamic **single-cell measurements**.
37 Such experiments are challenging, as they require efficient imaging and cell
38 segmentation-tracking methods, but are now possible at high throughput,
39 and with microfluidic control of nutrient exchange. Used in combination
40 with reporters of molecular events and new theoretical models, they they
41 provide a unique opportunity to build a new basis for understanding the cell
42 cycle.

43 This data will be more and more accessible in the coming years, but the
44 recent literature leaves us with a wealth of conclusions and models that seem
45 incompatible and incoherent. The main hypotheses that we put forward in
46 this opinion article is that (i) this apparent incoherence can be overcome and
47 is not due to intrinsic limitations of the approach, and (ii) it is a smoking
48 gun for the need of more comprehensive and precise quantitative methods in
49 both data analysis and theoretical descriptions. Such tools are necessary to
50 properly handle the large amount of data and, most importantly, to formulate

51 and test falsifiable models of cell cycle control. This approach can be applied
52 broadly, including eukaryotes [4, 5, 6].

53 **2. The average cell is not the typical single cell**

54 From the pioneers of quantitative bacterial physiology of the “Copen-
55 hagen School” [7], empirical observations in terms of quantitative relations
56 between physiology-related variables averaged over large populations have
57 been used to infer specific control mechanisms of the cell cycle [8, 7]. The
58 problem is that the average cell behaviour does not correspond necessarily to
59 the typical behaviour of single cells. Therefore, models based on population
60 averages have limitations, and ought to be revisited and tested with single-
61 cell data. The classic example is the model proposed by Donachie [2] in the
62 1960s, stating that DNA replication is initiated at a critical mass per repli-
63 cation origin. As we will discuss, although appealing and describing properly
64 the measured cell-cycle response to changes in growth media, this model may
65 be insufficient to describe recent single-cell measurements. In other words,
66 there are unique specific behaviors of single live cells that are obscured if we
67 average everything.

68 For the cell cycle to progress, events related to DNA replication and **seg-**
69 **regation**, metabolism, growth and cell division must occur in a specific time
70 order for each cell (across many divisions along lineages [9, 10]), despite con-
71 siderable molecular noise and variability of parameters. This hierarchy has
72 major impact on single cells, but may be missed drawing data from popu-
73 lation averages. For example, a missed **septation** due to late segregation
74 may lead to failure of cell division, formation of a filamentous cell and subse-

75 quent rescue, which can be accompanied by a non-symmetric division, with
76 consequences on the balance of cell size, DNA amounts and cell-cycle reg-
77 ulators observable over several generations. However, these events typically
78 affect a small fraction of the population, and their consequences would not
79 be observable in population averages, unless most of the population becomes
80 filamentous. Therefore, dissecting such a cascade of errors and controls would
81 be impossible without a single-cell view, since the complex temporal inter-
82 play of several concurrent processes and the important role of **stochasticity**
83 are hidden by population averages

84 **3. From phenomenological to mechanistic models**

85 A clear sign that the application of high-throughput single-cell techniques
86 is effective comes from recent work. These measurements have already un-
87 veiled the stochastic nature of metabolism and resulting growth [11], intrigu-
88 ing universal properties of the joint distribution of cell size and interdivision
89 times [12, 13], as well as an effective principle where cells add, on average,
90 a constant volume to their initial one every cell division (sometimes called
91 the **adder mechanism**) [14, 15, 12, 16], which is consistent with long-term
92 **homeostasis** of the cell-size distribution in a population.

93 However, the molecular basis of this observation remains unknown. In-
94 deed, several phenomenological models can in principle reproduce the empir-
95 ical observation of a constant average added size. For example, a “concerted”
96 control of cell division based on cell size and on time [17, 13, 18, 19] as well
97 as a completely different mechanism based on the ratio between cell surface
98 and volume [20] can both reproduce this behaviour. Thus, the recent papers

99 leave us with a rather obscure picture. Clearly, part of such differences may
100 be due to sensitivity of measurements to differences in growth conditions, ge-
101 netic background, experimental and analysis methods, and so on. However,
102 we argue that insufficient integration of theoretical approaches and data also
103 plays a large role, and the lack of a general theoretical framework to inter-
104 pret the data (and compare and falsify models) also limits the experiments.
105 Therefore, it is necessary to link more closely theoretical models to data on
106 one side and to molecular mechanisms on the other.

107 **4. Cell-cycle intervals**

108 To move our mathematical descriptions towards more specific biological
109 mechanisms, a first step is to focus the analysis on specific cell cycle events
110 that have been directly linked to molecular controls. Indeed, a common way
111 to describe qualitatively the progression of the cell cycle [1, 22, 23] is to
112 define **cell-cycle intervals** (Fig. 1), by key landmark events (e.g., replica-
113 tion, formation of the Z-ring, septation, etc.), and establishing their rela-
114 tive timing and connection with global observables such as cell growth rate,
115 size, total protein concentration, as well as with concentration of selected
116 metabolic or cell-cycle proteins (e.g., a reliable reporter of the initiator pro-
117 tein DnaA [24, 25]).

118 Note that cell-cycle intervals may span multiple consecutive generations,
119 and are not necessarily defined within two consecutive divisions. For exam-
120 ple, it might make sense to consider the events of completion of a successful
121 segregation and onset of septation in one cycle, and link them to the event of
122 replication initiation in the following one, or consider the period between ter-

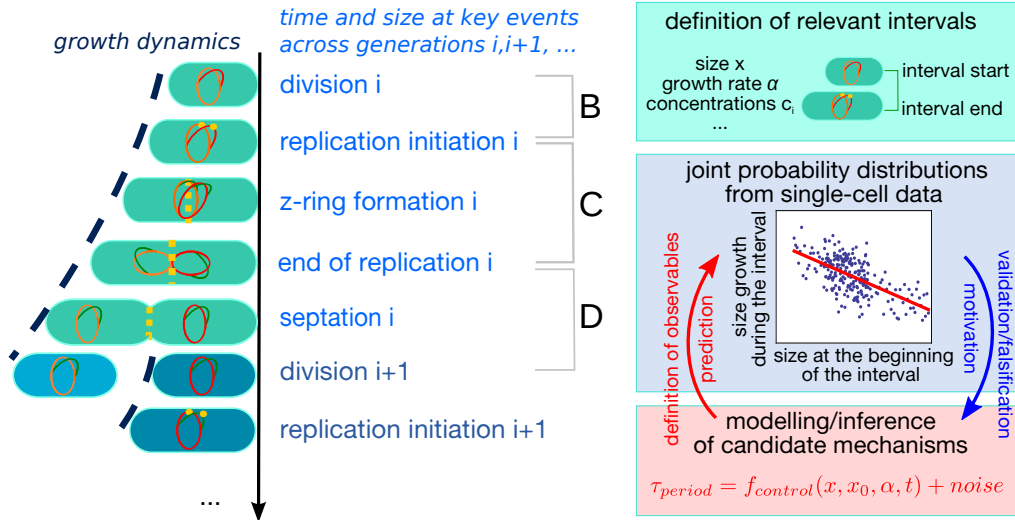


Figure 1: Key events in the *E. coli* cell cycle define cell-cycle intervals subject to stochastic variation and exerting homeostatic control. The left panel illustrates some of the key cellular events (replication cycle, Z ring formation, septation, etc.) which may be used to define intervals across generations (indexed as $i, i+1, \dots$). Cell-cycle intervals may not span just the time between two cell divisions, but can be defined across consecutive generations. The right panels illustrate the outlook for future analyses supported in this opinion paper. First (top panel), cell-cycle intervals are defined, and values of key variables (including size x) are collected at the beginning of each interval. Second, joint distributions of measured variables are used to motivate a mathematical model. The example plot is the joint distribution of size growth and initial size in an interval, conventionally used to detect size homeostasis [21]. Third (bottom panel) mathematical models define key observables and falsifiable predictions to test in the data. The formula in the example relates the duration of an interval τ to stochasticity (“noise”) due to intrinsic cell-to-cell variability of cellular parameters, and homeostatic control based on measurable variables. Reciprocal feedback between falsifiable models and data helps identifying mechanisms and molecular players of cell-cycle progression.

123 mination and initiation (typically in the next generation), where ATP-DnaA
124 is supposed to increase [26, 27]. More trivially, it is well known that the
125 timing of replication, the “C period”, can be longer than the interdivision
126 time [1, 28], since fast-growing *E. coli* cells support multiple DNA replica-
127 tion rounds at the same time, and thus the replication initiation in one cell
128 cycle will lead to a complete chromosome in a subsequent cycle of a daughter
129 or grand-daughter cell. Reporters of at least some of the key players of the
130 cell-cycle are at hand, thanks to many previous studies characterizing several
131 aspects of the *E. coli* cell cycle [29, 30, 31].

132 The cellular process or event defining cell-cycle intervals can both cause
133 an increase of cell-to-cell variability in size (by an intrinsic stochasticity due
134 to biochemical noise, e.g., the timing of the completion of replication for the
135 C period varies from cell to cell) and correct for this increase in variability
136 by enacting decisions on the cell cycle (for instance by compensatory effects
137 that suppress variability, e.g., B period duration may be shorter on aver-
138 age for cells that are born larger.) Cells adjust the cell-cycle to respond to
139 specific needs (e.g. conditioning division to successful nucleoid segregation),
140 creating a structure of correlations between interval durations and measur-
141 able parameters. While we still have to fully learn how to decipher such
142 trends, we know that they enable the production of testable (and falsifiable)
143 quantitative mathematical descriptions of the cell cycle.

144 Note that organizing the cell cycle into discrete events may be difficult,
145 and this simplification has its limitations. For example intervals might be
146 hard to define for chromosome segregation, which is a multi-step process [32].
147 Equally, reporters of expression of cell-cycle proteins do not define intervals

148 per se, but they rather exhibit temporal oscillations or specific spatial orga-
 149 nizations. More in general, protein expression and spatial distributions can
 150 be correlated with cell cycle processes and events.

151 **5. Studying single cells can challenge long-standing hypotheses.**

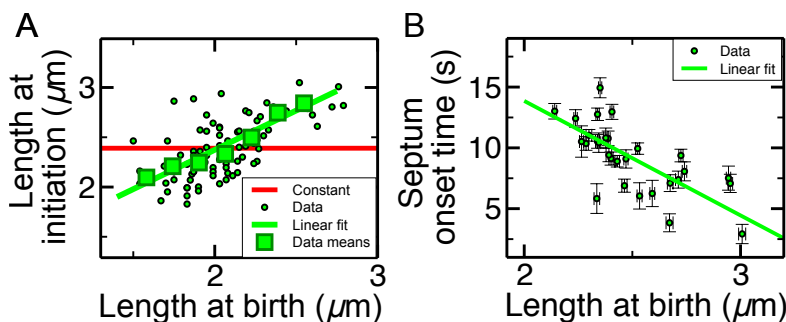


Figure 2: Examples of insights from correlation analysis of cell-cycle intervals. A: Available data for replication initiation in single cells challenge the hypothesis of initiation at a critical cell size (mass). The plot (data from ref. [18]) shows the cell size at replication initiation (estimated by the appearance of SeqA-GFP foci) versus the initial cell size (estimated by cell length, cell width being constant across cells). Each circle corresponds to a different cell cycle. A critical mass model (red line) would predict that the initiation size is the same regardless of size at birth. Instead, while there is some control on size, cells tend to be larger at initiation if they are born larger (green, squares are binned averages of data, solid line is a linear fit). B: Septum onset time enforces size homeostasis. The plot (data from ref. [33]) shows the septum onset time (measured by cell shape segmentation [34]) versus the initial cell size. A pure characteristic septation time would show no correlation with length at birth, but the existence of a correlation suggests a correction mechanism. A recent study on perturbations of volume and surface growth rates supports this observation [20].

152 A number of recent studies have produced data that are already chal-
 153 lenging existing models, and highlight the importance of further investiga-

154 tions [33, 23, 18]. One example is the “licensing hypothesis” for replication
155 initiation [23], which, based on observations on single cells, proposes that
156 septation or occurrence of cell division may license (by activating the ori-
157 gin or releasing an inhibitory signal) the chromosomes for the next round of
158 replication initiation (and unlicensed origins cannot initiate).

159 Concerning the timing of replication initiation and cell division, Donachie [2],
160 based on population data [35, 1], proposed that DNA replication is initiated
161 at a critical mass per replication origin. Notably, this author was very aware
162 that the critical mass hypothesis applies *on average*, in response to changes
163 in the external conditions, and need not be valid for single cells in a fixed
164 condition. Additionally, theoretical descriptions that do not comply with the
165 critical mass hypothesis are present in the literature. For example, a recent
166 modeling study [36] argues that initiation may occur after a constant size
167 has been added between consecutive initiations.

168 Two recent studies used fluorescent labeling of replication forks to mea-
169 sure replication initiation in single cells [18, 19]. Both studies show size
170 compensation in the B period, i.e., cells that are born larger than average
171 initiate earlier. This supports a link between replication initiation and size
172 homeostasis, by initiation following cell size, by initiation controlling cell
173 division, or both.

174 A similar correlation with size was observed in one study for the D-period
175 between termination and division [18]. Whether size compensation at initia-
176 tion is governed by a critical size remains incompletely resolved. Both data
177 sets show that initiation size increases with initial size in slower growth con-
178 ditions (Fig. 2). The Wallden *et al.* data at faster growth rate suggest that

179 initiation size is independent on initial size, leading them to argue in favor
180 of a constant initiation volume model also for the slower growth rates [19],
181 and attributing the correlation to missed initiation events before birth, in
182 the mother cell. Initiations could occur before cell division without being
183 detectable by SeqA foci, or be inhibited by a licensing-like phenomenon (see
184 above and ref. [23]), visible. However, these events of initiation before divi-
185 sion are not clearly characterized in current studies. In comparing different
186 studies, one must also consider possible effects of growth conditions, strains
187 used, and labelling schemes: one can for instance label all SeqA proteins [19],
188 or only a fraction of them [18], or label different proteins involved in the repli-
189 cation process, such as DnaQ [19].

190 Thus, new tests and measurements are necessary, together with theoreti-
191 cal frameworks to clearly test or falsify alternative models. Importantly, the
192 interpretation differences between the two studies is also reflected in differ-
193 ences in the mathematical models that were used and shown to be consistent
194 with the data. While one model assumes a control without a precise critical
195 mass for the B period and a size-coupled D period [18], the other assumes a
196 critical mass at initiation and a duration of the sum of C and D period that
197 is coupled to single-cell growth rate and not cell size [19]. A third model,
198 mentioned above, suggests a constant added size per origin between initi-
199 ations [36]. Of course, not all predictions of these models are expected to
200 coincide and and it would be fruitful to compare them in further detail.

201 A second example of useful information from cell-cycle intervals at the
202 single-cell level is the hypothesis of a role of septum formation in size home-
203 ostasis. Single-cell analysis (Fig. 2) indicates that the cell-cycle interval from

204 cell birth to onset of septation (measured by cell segmentation) may be size-
205 dependent [33]. More recent results [20] have led to speculation that septum
206 formation may be the main (“rate limiting”) checkpoint in deciding cell di-
207 vision in most conditions. A size-coupled septation mechanism corresponds
208 to the hypothesis that replication might not be the driver, or the only driver
209 of the coupling between cell division and size (as assumed in the models of
210 refs [36, 19, 18], whereas the model by Harris and Theriot [20] takes the
211 complementary assumption that septation is the only driver of cell division).
212 Conversely, the cell-cycle interval defined by the timing between onset of
213 septation and cell division fluctuates around a constant value, independent
214 of the total interdivision time, much like the C period [33].

215 In conclusion, these studies illustrate the gaps of knowledge regarding the
216 cell cycle at the single-cell level, provide preliminary answers, and show the
217 potential of correlating events and processes in single cells.

218 **6. How do cell-cycle intervals add up to produce size homeostasis** 219 **and cell-cycle control?**

220 Deeper knowledge of the most relevant cell-cycle intervals, reflecting key
221 processes such as replication cycle and Z-ring contraction, will help in answer-
222 ing how different controls contribute to size homeostasis, a constant added
223 size, and the observed scaling of cell sizes and interdivision times [13]. From
224 the biological viewpoint, characterizing the cell cycle is a broader aim than
225 mere characterization of cell-size homeostasis, but understanding the link
226 between cell-size distribution, metabolism and key molecular determinants
227 may have important implications. Taking the example of the observed con-

228 stant added size [12, 15], one may link this behavior to a classic “initiator”
229 model [37] where the key step (replication initiation) is triggered by the ac-
230 cumulation of an initiator protein to a constant copy number, and not a
231 constant concentration, which is compatible with the observation that the
232 total amount of active DnaA appears to be relevant for initiation timing in
233 *E. coli* [29]. However, several processes may contribute to the decision to
234 divide [38]. Besides the process of replication initiation by DnaA [26, 27],
235 the division triggering of the Z-ring [22, 39], conditioned on successful segre-
236 gation [40], as well as metabolic cues [30, 41] and septum synthesis [20] have
237 all been linked to cell division.

238 Analysis of the concerted action of these control mechanisms should show
239 whether the decision to divide is captured by a single ”rate limiting” prin-
240 ciple [20], whether different controls may be rate limiting in different condi-
241 tions [19], or whether parallel controls are active on overlapping time scales.
242 Incidentally, none of the intervals defined by DNA replication (B,C,D peri-
243 ods) appear to obey constant added size in slow-growing cells, but a model
244 incorporating the observed couplings of net elongation during B,C,D, with
245 size at the beginning of each period [21] does reproduce the overall constant
246 added size behavior [18].

247 Cells might want to try to add a constant size for many reasons, such
248 as (i) an architectural constraint (due, e.g., to cell-wall growth [20]), (ii)
249 a consequence of how the control mechanism is effected at the molecular
250 level [37, 12] or (iii) by a circuit that measures absolute size, but happens to
251 show this behavior [19]. A complementary possibility is that observations
252 such as the constant added size or the scaling of size and doubling time

253 fluctuations could be the result of selection, such as optimization for colony
254 growth or lineage expansion or ecosystem-level interactions [42], or avoidance
255 of detrimental effects such as waste accumulation.

256 **7. Concluding remarks and future perspectives.**

257 Perhaps the most important feature of the future direction we propose
258 is that it is fully quantitative, and benefits from integration and feedback
259 between theoretical predictions and experiments that is not yet achieved in
260 the field. We see this area as a major challenge for the applications of statis-
261 tical physics to biology. Precise quantitative measurement of the key players
262 with sufficient statistics (see Outstanding Questions) can be achieved, with
263 the ultimate goal of producing mathematical equations capturing coherently
264 all observed behaviors and able to predict phenotypes at the single-cell level.
265 New theoretical work should compare alternative mechanisms, identify which
266 observables are central to distinguish, and determine the precision/statistics
267 needed in the experiments for optimal measurements [43].

268 A quantification of cell-cycle intervals in single cells can be complemented
269 by their change in response to the external conditions, mutations, and other
270 perturbations such as arresting replication, depleting DnaA, overexpressing
271 both functional and non-functional proteins, etc. [20, 44, 45, 46]. For ex-
272 ample, nutrient shifts were used classically to look at cell division dynam-
273 ics [47, 48], but they can potentially give a wealth of further information in
274 single cells. A further challenge will be to understand adaptation behavior in
275 non-steady conditions and linking this dynamic behavior to the homeostatis
276 observed in fixed environments.

277 Finally, focusing on cell-cycle intervals that are closely linked to molecular
278 mechanisms would give us a minimal but fully mechanistic description of
279 the available data. Important limitations are apparent as well. First, the
280 tools for linking conditional dependencies between experimental observables
281 to mathematical models still need to be fully developed. Second, correlations
282 do not necessarily reveal causality. Third, correlations may be sensitive to
283 external conditions and genetic background. However, we believe that such a
284 development, combined with molecular biology and biochemistry, will bring
285 us closer to a mechanistic description of the cell cycle at the single-cell level.

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290 Science Program Organization, grant RGY0070/2014.

291 **Outstanding Questions Box**

292 What are the key molecular events in the cell cycle of single *E. coli* cells
293 and how do they compromise or promote homeostasis of basic parameters
294 such as cell size, protein concentration, and DNA copy number?

295

296 How are metabolic signals and housekeeping events (replication, segrega-
297 tion, etc.) integrated to decide when to divide?

298

299 Does the observed constant added size mechanism emerge from the inte-
300 gration of multiple decisions or is it the result of a single process?
301

302 **TRENDS BOX**

303 [900 characters / 3-5 bullet points]

304 The cell cycle is stochastic due to intrinsic cellular noise, affecting decision-
305 making related to key steps (i.e., initiation of replication, chromosome seg-
306 regation, Z-ring contraction and septation)

307

308 Recent high-throughput single-cell measurements of growing *E. coli* show
309 a constant average added size between consecutive cell divisions.

310

311 Similar measurements allowing the full stochastic unraveling of the *E. coli*
312 cell cycle will likely become available in the coming years.

313

314 These data will open new perspectives and challenge classic views, start-
315 ing from the long-standing hypothesis that a critical mass per origin triggers
316 replication initiation.

317

318 **GLOSSARY**

319 **Adder mechanism:** The hypothesized mechanism by which *E. coli* cells
320 tend to add a constant volume or mass to the initial size to decide the moment
321 of cell division. This mechanism enforces size homeostasis [15, 12]

322 **Cell-cycle interval:** Defined here as the period of time between two key
323 events in the cell cycle (Fig. 1). For example, three cell-cycle intervals are
324 classically defined with respect to DNA replication: the B,C,D sperated by
325 replication initiation and the end of replication.

326 **DnaA:** ATP-ase protein that accumulates in its active ATP-bound form
327 to a threshold value during the cell cycle inducing DNA melting by binding
328 cooperatively to the origin(s) and thus triggering initiation of DNA replica-
329 tion [26].

330 **Homeostasis:** The process through which single cells control key vari-
331 ables (such as size, concentrations) in order to ensure their stability along
332 lineages. There is, in general, a difference between homeostasis in fixed con-
333 ditions and the average response to a perturbation.

334 **Population measurements:** Measurements of average quantities over
335 large cell populations. Most of growth-related laws in bacterial physiology
336 are based on such measurements [8], typically for exponentially growing pop-
337 ulations. For example, the typical population estimate of the average cell size
338 consists in a measurement of optical density divided by a cell count [7].

339 **Replication initiation:** The start of DNA replication, defining the

340 end of the B period in bacteria, and corresponding to the G1/S transition in
341 mammalian cells.

342 **Segregation:** The process of disentanglement and separation of dupli-
343 cated chromosomes necessary to ensure a chromosome copy to each daughter
344 cell.

345 **Septation:** Formation of a cell wall that constricts the cell (approxi-
346 mately in the middle for symmetrically dividing bacteria like *E. coli*) and
347 leads to new cell poles.

348 **Single-cell measurements:** Experiments following dynamically many
349 cells with single-cell resolution, monitoring size, shape and fluorescent probes,
350 and allowing to quantify the cell-to-cell variability and correlations.

351 **Stochasticity:** In the context of cell cycle events, represents the ten-
352 dency of cell-cycle progression to be different in each individual cell, due to
353 values of internal variables (e.g. key protein amounts or concentrations) and
354 molecular noise. As a consequence, mathematical models have to describe
355 the cell-cycle progression as a stochastic process, typically representing the
356 interplay of cell-to-cell variability and homeostatic control.

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