

WHAT'S NEW IN INTENSIVE CARE



Intensive care medicine in 2050: clinical trials designs

M. Gasparini¹ and S. Chevret^{2,3*}

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Background

For a long time, clinical trials have been designed in a fairly standard way. In phase III randomized clinical trials (RCTs), widely considered the top of the evidence pyramid, each patient typically has a 1:1 chance of being allocated to the experimental or the control treatment. The scheme involves a large number of patients, often due to the modest expected benefits, the so-called “effect size”. Such a factor has the greatest impact on both sample size and power computations, and it has been reported to explain the failure of most RCTs in critical care medicine where the desired effect size (10.1% on average) is often largely above the observed one (1.4% on average [1]). Even large sample sizes are no guarantee of positive findings, with small observed benefits possibly explained by several problems, such as protocol deviations or unscheduled crossovers diluting treatment effects [2] as well as true negative findings. In addition, the large sample sizes required in RCTs may limit their feasibility due to excessive cost and/or time. Effectiveness of clinical trials might be improved by adopting a more integrated approach which increases flexibility and maximizes the use of accumulated knowledge to reduce sample sizes and to increase effect sizes for selected patient subpopulations.

Using supplementary evidence

Merging the strength of RCTs that are conducted on homogeneous populations and observational studies, where less homogeneous samples are used, appears promising. In this regard, trials that prospectively integrate both RCT and real-world data would be of interest.

As an example, the “mixed randomized trial” [3] has been proposed to meet the evolving demands of regulators faster than multiple separate phase III/IV individual trials. This combined approach first randomizes patients to RCT, pragmatic trial, or observational study, then to treatment groups either randomly (for the first two arms) or as per local clinical practice (for the latter arm). Though promising, this new multi-tiered trial design requires thoughtful planning and further validation.

In the ICU, the complexity of critical illness syndromes is a fundamental justification for the adoption of a personalized approach to research [4]. Thus, identifying effectively patients who will benefit from treatment by refining critical illness types has been the motivation for innovative proposals of the so-called “precision medicine”, which aims to tailor the treatments given to patients according to their characteristics. This change of paradigm has been mostly beneficial in the oncology setting, where widespread changes in clinical practice for diagnosis and treatment have been increasingly based on genomic features [5]. A number of Phase II and Phase III clinical trial designs have been proposed to test the effectiveness of a biomarker-guided approach to treatment. Pivotal clinical trials of such therapies are based on innovative adaptive and non-adaptive designs.

Innovative designs

Non-adaptive designs

In oncology, biomarker strategy designs allocate patients with certain histological features (“umbrella” trials) or certain specific genomic alterations (“basket” trials) to targeted treatments according to the value of the genetic features or, more generally, biomarkers [6]. While umbrella trials allocate patients to many different treatment arms based on their specific biomarker, in contrast, basket trials test the effect of one drug on a single predictive biomarker in a variety of tumour types. In the light

*Correspondence: sylvie.chevret@univ-paris-diderot.fr

² AP-HP, Saint-Louis Hospital, Biostatistics Team, Paris, France

Full author information is available at the end of the article

of what has been done in oncology, precise information about ICU subsets could lead to targeted treatments or interventions in pre-specified subpopulations that could be assessed similarly.

Adaptive designs

Compared to standard designs, adaptive designs can make clinical trials more flexible by utilising results accumulating in the trial to modify the trial course in accordance with pre-specified rules, aiming at improving the study power and reducing the sample size and trial cost [7, 8]. Their differences with standard designs can be summarized into two main points.

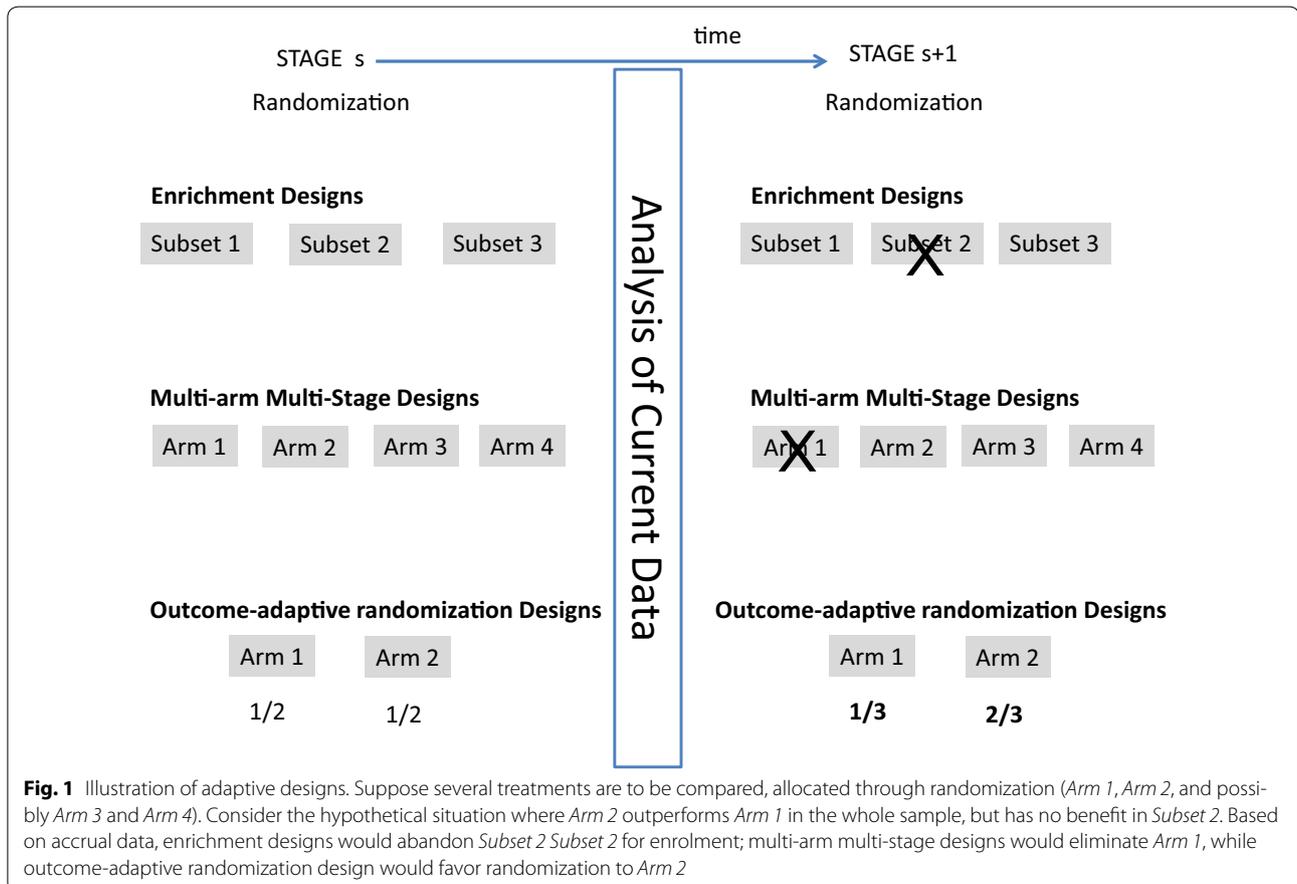
First, besides stopping the whole trial at an early stage for success or lack of efficacy, like interim analyses of standard designs, adaptations are extended to any points of the design [9]. This can be illustrated in three examples (Fig. 1).

- Enrichment designs: While standard designs enrol a broad range of patients and often run post hoc subset analyses to determine those patients who may benefit from the new treatment, adaptive designs allow the

eligibility criteria of the trial to be adaptively updated during the trial, excluding patients who appear unlikely to benefit from the new treatment [10]. They have been proposed for potentially enhancing clinical trials in sepsis [11, 12].

- Multi-arm multi-stage (MAMS) designs: MAMS explore multiple treatments, doses, durations or combinations with options to ‘drop losers’ or ‘select winners’ early [13]. They intend to eliminate poorly performing arms at the early stages; only treatments showing a predefined degree of advantage against a control treatment are allowed through to the later stages.
- Outcome-adaptive randomization: While standard designs use a fixed allocation ratio, these designs update random allocation probabilities, so that more patients are allocated to the most promising strategy as evidence accumulates. They remain controversial [14].

Secondly, these changes in the trial design have to be pre-specified at the protocol stage to maintain the validity and integrity of the trial. They are thus different from unplanned ad hoc modifications, a deprecated practice



[8]. Adaptive designs either use innovative tests which use more flexible decision rules but still preserve type I errors, or Bayesian inference. In the Bayesian framework, prior information (from previous trials, scientific research or expert opinion) is combined with current information during the trial. There are no traditional hypothesis tests, the concept of type I error adjustment is foreign to this way of thinking, and multiple looks at the data is (statistically) not a problem. Thus, Bayesian statistics and adaptive designs often go hand in hand, and many adaptive designs are currently run in this framework [15].

Conclusions

Originally proposed in oncology to assess many treatments and biomarkers, innovative trial designs have raised many controversial discussions from the beginning, and are still underused and surrounded by misconceptions [8]. Nevertheless, they appear to provide a possible blueprint for therapeutic development in the ICU. Given their significant complexity, multidisciplinary collaborations and team science appear a key to the success of these new design strategies in the ICU.

Author details

¹ Department of Mathematical Sciences, Politecnico di Torino, Turin, Italy.

² AP-HP, Saint-Louis Hospital, Biostatistics Team, Paris, France. ³ Paris Diderot University, Inserm, ECSTRRA Team, Paris, France.

Compliance with ethical standards

Conflicts of interest

The authors declare that they have no conflict of interest.

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References

1. Abernethy SK, Richards DR, O'Brien JM (2010) Delta inflation: a bias in the design of randomized controlled trials in critical care medicine. *Crit Care* 14:R77. <https://doi.org/10.1186/cc8990>
2. Porcher R, Lévy V, Chevret S (2002) Sample size correction for treatment crossovers in randomized clinical trials with a survival endpoint. *Control Clin Trials* 23(6):650–661
3. Alsop J, Scott M, Archey W (2016) The mixed randomized trial: combining randomized, pragmatic and observational clinical trial designs. *J Comp Eff Res* 5(6):569–579. <https://doi.org/10.2217/ceer-2016-0034>
4. Maslove DM, Lamontagne F, Marshall JC, Heyland DK (2017) A path to precision in the ICU. *Crit Care* 21:79. <https://doi.org/10.1186/s13054-017-1653-x>
5. Renfro LA, An MW, Mandrekar SJ (2017) Precision oncology: a new era of cancer clinical trials. *Cancer Lett* 387:121–126. <https://doi.org/10.1016/j.canlet.2016.03.015>
6. Kelloff GJ, Sigman CC (2012) Cancer biomarkers: selecting the right drug for the right patient. *Nat Rev Drug Discov* 11(3):201–214
7. Bhatt DL, Mehta C (2016) Adaptive designs for clinical trials. *N Engl J Med* 375(1):65–74. <https://doi.org/10.1056/nejmra1510061>
8. Pallmann P, Bedding AW, Choodari-Oskooei B, Dimairo M, Flight L, Hampson LV, Holmes J, Mander AP, Odondi L, Sydes MR, Villar SS, Wason JMS, Weir CJ, Wheeler GM, Yap C, Jaki T (2018) Adaptive designs in clinical trials: why use them, and how to run and report them. *BMC Med* 16(1):29. <https://doi.org/10.1186/s12916-018-1017-7>
9. Thorlund K, Haggstrom J, Park JH, Mills EJ (2018) Key design considerations for adaptive clinical trials: a primer for clinicians. *BMJ* 360:k698. <https://doi.org/10.1136/bmj.k698>
10. Simon N, Simon R (2013) Adaptive enrichment designs for clinical trials. *Biostatistics* 14(4):613–625. <https://doi.org/10.1093/biostatistics/kxt010>
11. Wong HR, Lindsell CJ (2016) An enrichment strategy for sepsis clinical trials. *Shock* 46(6):632–634. <https://doi.org/10.1097/SHK.0000000000000693>
12. Talisa VB, Yende S, Seymour CW, Angus DC (2018) Arguing for adaptive clinical trials in sepsis. *Front Immunol* 9:1502. <https://doi.org/10.3389/fimmu.2018.01502>
13. Sydes MR, Parmar MK, Mason MD, Clarke NW, Amos C, Anderson J et al (2012) Flexible trial design in practice—stopping arms for lack-of-benefit and adding research arms mid-trial in STAMPEDE: a multi-arm multi-stage randomized controlled trial. *Trials* 13(1):168
14. Thall P, Fox P, Wathen J (2015) Statistical controversies in clinical research: scientific and ethical problems with adaptive randomization in comparative clinical trials. *Ann Oncol* 26(8):1621–1628
15. Berry SM, Carlin BP, Lee JLL, Muller P (2010) Bayesian adaptive methods for clinical trials. CRC, Boca Raton