Invited Commentary:
Comparing the Independent Segments Procedure with Group Sequential Designs

Daniël Lakens
Eindhoven University of Technology

Cite as:

Lakens, D. (2021). Invited commentary: Comparing the independent segments procedure with group sequential designs. *Psychological Methods*, 26(4), 498–500. <http://dx.doi.org/10.1037/met0000400>

Correspondence can be addressed to Daniël Lakens, Human Technology Interaction Group, ATLAS 9.042, PO Box 513, 5600MB Eindhoven, The Netherlands. E-mail: D.Lakens@tue.nl. This work was funded by VIDI Grant 452-17-013 from the Netherlands Organization for Scientific Research.

Abstract

Psychological science would become more efficient if researchers implemented sequential designs where feasible. Miller and Ulrich (2020) propose an independent segments procedure where data can be analyzed at a prespecified number of equally spaced looks while controlling the Type 1 error rate. Such procedures already exist in the sequential analysis literature, and in this commentary I reflect on whether psychologist should choose to adopt these existing procedure instead. I believe limitations in the independent segments procedure make it relatively unattractive. Being forced to stop for futility based on a bound not chosen to control Type 2 errors, or reject a smallest effect size of interest in an equivalence test, limit the inferences one can make. Having to use a prespecified number of equally spaced looks is logistically inconvenient. And not having the flexibility to choose α and β spending functions limit the possibility to design efficient studies based on the goal and limitations of the researcher. Recent software packages such as rpact (Wassmer & Pahlke, 2019) make sequential designs equally easy to perform as the independent segments procedure. While learning new statistical methods always takes time, I believe psychological scientists should start on a path that will not limit them in the flexibility and inferences their statistical procedure provides.

Sequential analyses make it possible for researchers to test hypotheses efficiently. Sequential analyses are extremely well-established in some disciplines, such as medicine, but rarely used in other disciplines, such as psychology. Given that all scientists face resource constraints, and sequential analyses reduce the average sample size that needs to be collected when testing hypotheses, it is surprising sequential analyses are not used more widely. Miller and Ulrich (2020) provide a welcome reminder to psychological scientists that they really should adopt sequential analyses more often.

All sequential analysis procedures work by lowering the alpha level at each look in such a way that the overall alpha level is maintained. Miller and Ulrich (2020) propose choosing a strong and weak alpha level, where data collection stops to reject H_0 when $p < \alpha_{\text{strong}}$, or fail to reject H_0 when $p > \alpha_{\text{weak}}$. At the final look, H_0 is rejected when $p < \alpha_{\text{weak}}$. An important difference with traditional sequential analyses is that the independent segments procedure calculates p -values based on the data from each segment. With three looks in a two independent groups design, and 25 participants in each group, the three independent t -tests in the independent segments procedure are based on 50 observations each, where traditional sequential analyses combine the data for each interim analysis.

The independent segments procedure has some limitations compared to traditional sequential analyses, that are not sufficiently highlighted in the manuscript by Miller and Ulrich. First, it forces researchers to terminate a study early if a high p -value is observed, and to fail to reject H_0 if $p > \alpha_{\text{weak}}$. This limits users to applying a decision rule to stop for futility that is based on a value that controls the overall Type 1 error rate. Traditional sequential analyses allow researchers to choose whether or not to stop for futility, and allow researchers to design studies where a study is terminated either based on a desired the Type 2 error rate, or because a smallest effect size of interest is rejected in an inferiority or equivalence test (Jennison & Turnbull, 2000). This prevents researchers from incorrectly concluding their prediction was not supported based on a p -value larger than some alpha level, a common problem in null hypothesis significance testing. Miller and Ulrich (2020) argue: “This is probably not a serious limitation in practice, because most researchers do seek to show that hypothesized effects are present”. Although this is might be true, as a field we do not want to enable researchers in their desire to ignore how their predictions might be proven wrong. Stopping for futility has benefits (e.g., lower average sample sizes) and downsides (e.g., lower power, for discussions, see

Schoenfeld & Meade, 2005; Schüler et al., 2017), and researchers should have the choice to stop at earlier looks, or not. Furthermore, researchers should be able to falsify their predictions, for example by using equivalence tests. The independent segments procedure too strongly limits researchers in the statistical inferences they can draw, while this flexibility exists in traditional sequential analyses.

Second, the segmented procedure requires researchers to specify the number of looks in advance (e.g., commit to looking at most three times), and the procedure requires researchers to collect equally spaced looks (e.g., each look consists of 50 additional participants). In the 1980's, the sequential analysis literature realized these two constraints are often too restrictive to make sequential analyses logistically workable. It is often impossible stop the data collection, analyze the data, and decide whether to continue or not, after for example exactly 50 participants. Alpha spending functions were created to overcome these limitations (Lan & DeMets, 1983). Alpha spending functions give researchers the flexibility to look when logistically convenient, and to skip or add looks as needed, while controlling error rates. There might be cases where data collection can be tightly controlled (e.g., online surveys), but psychologists should in general benefit from the flexibility sequential analyses provide.

The independent segments procedure is conceptually and mathematically similar to a sequential design with a Pocock α -spending function and Pocock β -spending function. I provide code¹ that allows R users to compare the independent segments procedure with a sequential design using α and β Pocock spending functions. The independent segments procedure performs better than this specific type of sequential design when the study design is severely underpowered, because it stops more aggressively. Sometimes it requires less observations, but this comes the cost of lower power. Other times, sequential designs provide more power with the same sample size. This leads to the third limitation of an independent segments procedure: It mimics one specific type of sequential design, without giving researchers the flexibility to choose between α and β spending functions (e.g., Pocock, O'Brien-Fleming, Wang & Tsiatis, or Haybittle & Peto design). The flexibility to choose a spending function allows users to optimize their study design given specific goals and limitations.

¹ <https://gist.github.com/Lakens/68ff55b4ab8b710cca129b5f5a11d501>

Whether the additional flexibility provided by sequential analyses is within reach of psychologists, or whether they will have to accept the limitations of simpler procedures, depends on the relative ease with which each method can be implemented by users. Are the three limitations in the independent segments procedure compensated by ease of use? The independent segments procedure is itself more difficult to implement than existing alternatives, such as applying a Bonferroni correction for each look. A Bonferroni correction is not optimal, but it is simple and valid (Wassmer & Brannath, 2016). Statistics is not unique in the trade-off between efficiency and ease of use. I personally do not see how choosing a weak and strong alpha level is easier than deciding upon an alpha spending function.

Beyond the choice of an alpha level for each look, designing an informative study requires choosing a sample size based on a desired power. For the independent segments method, a power analysis can be performed with the functions in the segHT package (which is not yet on CRAN, and has limited documentation). Although it is true that easy to use software for sequential analyses was lacking in the past (Albers, 2019), the well documented rpact R package (Wassmer & Pahlke, 2019), also available as an online Shiny app², is not noticeably more difficult to use than the code for the independent segments procedure, especially when we take functions for a-priori power analysis into consideration. Yes, the sequential analysis software has many more options, such as stopping for equivalence, conditional power analyses, a choice of α and β spending functions, and options to compute effect sizes, confidence intervals, and p -values adjusted for sequential designs. If the independent segments procedure is ‘simpler’, we can easily make sequential analyses simpler by limiting psychologists to a Pocock correction with equally spaced looks. Such cookbook recipes might have a function in getting people started, but users will quickly benefit from the greater flexibility sequential analyses provide.

In the end, we all want more researchers in psychology to adopt sequential analyses where feasible. This will allow the field to test hypotheses more efficiently. Whether researchers choose a simple Bonferroni correction, decide upon a decision rule after examining long-run error rates in a

² <https://rpact.shinyapps.io/public/>

simulation (Frick, 1998; Lang, 2017), use the independent segments procedure, or learn about sequential analyses, the field will become more efficient. Learning new techniques always takes time, but if you are going to enhance your understanding of sequential methods, start on a path that will not limit you in the flexibility and inferences your statistical procedure provides.

References

- Albers, C. (2019). The problem with unadjusted multiple and sequential statistical testing. *Nature Communications*, 10(1), 1921. <https://doi.org/10.1038/s41467-019-09941-0>
- Frick, R. W. (1998). A better stopping rule for conventional statistical tests. *Behavior Research Methods, Instruments, & Computers*, 30(4), 690–697. <https://doi.org/10.3758/BF03209488>
- Jennison, C., & Turnbull, B. W. (2000). *Group sequential methods with applications to clinical trials*. Chapman & Hall/CRC.
- Lan, K. K. G., & DeMets, D. L. (1983). Discrete Sequential Boundaries for Clinical Trials. *Biometrika*, 70(3), 659–663. <https://doi.org/10.2307/2336502>
- Lang, A.-G. (2017). Is intermediately inspecting statistical data necessarily a bad research practice? *The Quantitative Methods for Psychology*, 13(2), 127–140. <https://doi.org/10.20982/tqmp.13.2.p127>
- Miller, J., & Ulrich, R. (2020). A simple, general, and efficient procedure for sequential hypothesis testing: The independent segments procedure. *Psychological Methods*.
- Schoenfeld, D. A., & Meade, M. O. (2005). Pro/con clinical debate: It is acceptable to stop large multicentre randomized controlled trials at interim analysis for futility. *Critical Care*, 9(1), 34–36. <https://doi.org/10.1186/cc3013>
- Schüler, S., Kieser, M., & Rauch, G. (2017). Choice of futility boundaries for group sequential designs with two endpoints. *BMC Medical Research Methodology*, 17(1), 119. <https://doi.org/10.1186/s12874-017-0387-4>
- Wassmer, G., & Brannath, W. (2016). *Group Sequential and Confirmatory Adaptive Designs in Clinical Trials*. Springer International Publishing. <https://doi.org/10.1007/978-3-319-32562-0>
- Wassmer, G., & Pahlke, F. (2019). *rpact: Confirmatory adaptive clinical trial design and analysis* (2.06) [Computer software]. Retrieved from <https://CRAN.R-project.org/package=rpact>