## AM Last Page: Avoiding Five Common Pitfalls of Experimental Research in Medical Education

Mariëtte H. van Loon, MSc, PhD student, Ellen M. Kok, MSc, PhD student, Rachelle J.A. Kamp, MSc, assistant professor, Katerina Bohle Carbonell, MSc, PhD student, Jorrick Beckers, MSc, PhD student, Janneke M. Frambach, MA, PhD student, and Anique B.H. de Bruin, PhD, associate professor, Maastricht University

Experimental research is a scientific method that aims to provide evidence for cause-and-effect relations.<sup>1,2</sup> One or more independent variables are systematically manipulated to determine the effect(s) on a dependent variable while controlling other relevant factors. Often, the goal is to gain insight into underlying factors of an educational intervention. However, pitfalls are numerous in medical education experiments. Below, we present five common pitfalls and ways to avoid them.

Pitfall	Explanation of the problems and examples	Recommended solutions	Good example from the literature
Using an inappropriate control condition	<ul> <li>When you compare an experimental condition with a control condition, then you can attribute differences in outcome to differences between the conditions. If these conditions vary on too many elements, it is impossible to attribute outcomes to a specific element.</li> <li>If you compare Web-based learning with lectures, which differ in many aspects (e.g., learning pace, interaction with peers and teachers), you won't know which aspect(s) of these learning modes caused differences in outcomes.</li> </ul>	<ul> <li>Identify the crucial element of your intervention.</li> <li>Make the experimental and control conditions as similar as possible, except for the crucial element.</li> </ul>	Issa et al <sup>3</sup> compared a lecture that was designed according to multimedia principles with a lecture that was not designed according to these principles, but similar in every other aspect.
Failing to align your outcome measures to your research questions	<ul> <li>Outcome measurements should reflect the dependent variable(s) stated in your research question(s). If your outcome measures do not match your theory, your results do not answer your research questions.</li> <li>If you expect that students learn communication skills better when they have contact with real instead of simulated patients, you should measure communication skills rather than knowledge or perceptions about communication.</li> </ul>	<ul> <li>When designing a study, first clarify expected effects.</li> <li>Next, define how you can observe these effects.</li> <li>Then decide which instruments measure these effects.</li> </ul>	Cook et al <sup>4</sup> operationalized their dependent variable (learning outcomes) with two test types: a post- test after each module and a cumulative test.
Ignoring possible reactive effects of a pretest	<ul> <li>A pretest could provide information on baseline differences between participants. However, a pretest can cause participants to acquire relevant information. Therefore, the pretest can reinforce your intervention or have a direct effect on the dependent variable(s) that you measure with the posttest.</li> <li>If you ignore effects of a pretest that assesses prior knowledge, you won't know whether your results can be attributed solely to your intervention.</li> </ul>	<ul> <li>In a nonrandomized design:</li> <li>Let students do an irrelevant task between the pretest and intervention.</li> <li>Use existing data (e.g., grades) as a pretest.</li> <li>In a randomized design:</li> <li>Don't use a pretest.</li> </ul>	Hatala et al <sup>5</sup> randomly allocated students to one of two instructional approaches and didn't use a pretest to investigate the superiority of one of these approaches.
Not taking time-on-task into account	<ul> <li>It is likely that increased time spent on learning tasks yields increased learning outcomes. If you do not take this into account, it is impossible to attribute your outcomes solely to the variables you measured because they might be explained by differences in time-on-task as well.</li> <li>If you compare Web-based learning with lectures, the time-on-task is the actual time spent on the study activities.</li> </ul>	<ul> <li>Design conditions so that participants spend the same amount of time on the task.</li> <li>Control for time-on-task in statistical analyses if there are differences between conditions.</li> </ul>	In Mamede et al <sup>6</sup> the time participants were allowed to spend on each study case was the same for all conditions.
Confusing ecological and external validity	<ul> <li>Ecologically valid experiments do not necessarily have high external validity. Ecological validity is the extent to which your study approximates the real world. It often introduces elements (e.g., teacher characteristics, motivation) that mask or change effects, which, in turn, may compromise the external validity or generalizability of your study.</li> <li>If you investigate effects of an individual assignment in a classroom setting, student interaction can influence the effect and thus compromise external validity.</li> </ul>	<ul> <li>Focus on external validity instead of ecological validity.</li> <li>Achieve high external validity by conducting a well-controlled experiment that is repeated in different settings and populations.</li> </ul>	Marquard et al <sup>7</sup> investigated patient identification errors, controlling for the number and type of errors identified, during medication administration.

**References:** 

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Author contact: m.vanloon@maastrichtuniversity.nl