Commentary

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Explanation of Development of Disciplinary Skills

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Description

This review analyzes the learning reported in social science classroom interventions in primary and secondary school education over the last ten years. Thirty-three studies found in a scoping review were analyzed. They were analyzed using the two main perspectives of social sciences teaching and learning: each discipline individually and an interdisciplinary approach. Results show most interventions followed the disciplinary perspective, and amongst them, they mainly focused on the History subject. Most interventions explained the development of disciplinary skills, such as contextualization and historical thinking, giving less emphasis to the content and attitudes. Few studies are positioned in an interdisciplinary perspective, evidencing a significant research gap in social sciences learning. Literature indicates that if Social Sciences are taught and learned in an interdisciplinary manner, they have the potential to develop citizenship education. Therefore, teachers should move towards the interdisciplinary perspective to promote social thinking in their students.

Different Social Science Research Avenues and Proposes

The UN Decade of Ocean Science for Sustainable Development aims to tackle several challenges on the path towards more sustainable ocean futures. Its central objectives are to close knowledge gaps, increase the usability of scientific knowledge on the ocean, strengthen science-policy interfaces, and make oceanography fit for purpose. The quest for a reflexive turn within ocean science itself echoes many claims for more inclusive, diverse, and equitable research practices in the marine realm and provides an entry point for discussing the contribution of the social sciences to the UN Decade. This article examines different social science research avenues and proposes a research agenda detailing different entry points for unpacking the complex web of science-policy interrelations. First, we identify three research themes - reflexive ocean science, policy-relevant ocean science, and engaged ocean science- and nine research avenues where social science expertise is needed to close knowledge gaps. Second, we use the case of marine biodiversity to illustrate how to combine research into different avenues. Finally, the comprehensive study of ocean science's reflexive, political, and societal dimensions is an emerging field within ocean governance scholarship and deserves to receive increased attention from scholars interested in the conditions of transformative change. While evidence that contradicts a discipline's hard core assumptions is essential to scientific progress, its accumulation is made difficult by the protective nature of the middle range theories that protect it. For this reason, progress tends to be most common in response to external shocks that expose the limitations of traditional ways of thinking. Given the impact COVID-19 has had on our collective understanding of business, we propose that evidence against the hard core has reached the point where new thinking is necessary if we are to advance the field in productive ways. As the authors in this special issue demonstrate, such progress can be made by leveraging our intellectual roots in the social sciences. By looking to fields such as anthropology, sociology, jurisprudence, political science, and economics for inspiration, these authors use the current crisis as an opportunity to envision the future of family business scholarship. Advances in statistics and machine learning have the potential to rapidly expand the toolkit available to social scientists. The pace of change will depend on how social scientists weigh the costs and benefits of adopting new tools. Our review emphasizes four benefits to adoption: machine learning can amplify researcher coding, summarize complex data, relax some statistical assumptions, and target researcher attention. But many social scientists have yet to adopt machine learning tools. One reason machine learning methods have appeared infrequently thus far may be the appearance of high adoption costs, such as the time needed to learn new methods and the difficulties that arise when interpreting a complex model. Yet the increasing availability of open-source software and pedagogical materials means that these costs are quickly falling. One aim of our review is to contribute to the reduction in these costs by making new methods accessible; in this respect, we build on the excellent guidance provided by other recent review papers. A theme of our review is that the benefits of machine learning are likely to substantially outweigh the costs over time. Related to assumed costs, some social scientists may have a preconception that the adoption of machine learning methods requires a qualitative shift away from classical statistical methods. A second theme of our review is that there is no such qualitative shift. While the fields of "statistics" and "machine learning" have at times differed in their emphasis on various aspects of data analysis many of the key advances occur when these perspectives are brought together. What unites these fields is far greater than what divides them. For example, a generalized linear model is a standard statistical tool. Yet one could say that such a model "learns" a set of coefficients from data. A Least Absolute Shrinkage and Selection Operator version of that regression "learns" which of the covariates should enter the prediction function. As one moves from methods considered "classical statistics" toward methods considered "machine learning," one axis of change is away from imposed structure and toward a greater role for the data in learning. But this is a difference of degree rather than a difference of kind. Indeed, when a social scientist uses a statistical method, they can conceptualize that method as a specific case of a machine learning tool. We emphasize these connections and ground our review in classical statistics.

Conceptualize that Method as Specific Case

Hesitancy about the use of machine learning also stems from concerns that these methods are "black box," involving many parameters that are difficult to interpret. This concern may loom especially large among social scientists who are familiar with estimating regression models, placing the coefficients in a table, and interpreting those coefficients. Two responses address this concern. First, some machine learning methods response is that social scientists' comfort with "interpretable" regression coefficients is often misplaced. For example, researchers might interpret the coefficient as the "effect" of a particular variable. But such an "effect" may not correspond to any causal effect in the absence of additional assumptions. And if those assumptions hold, any machine learning prediction function can yield a similarly interpretable average effect estimator: predict the outcome for all units as observed, add one to the key predictor and make another prediction, difference the two, and average. Both approaches rely on the same causal assumptions, and under those assumptions both can yield an interpretable estimate of an average effect. An advantage of some machine learning methods is that the statistical assumptions may be more credible. This example illustrates a general point: a researcher who is precise about the quantity to be estimated can often engineer a machine learning approach to yield an interpretable estimate of that quantity.