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Fischer, Frank; Vogel, Freydis; Bodemer, Daniel; Chernikova, Olga; Cress, Ulrike; De Wever, Bram; Eberle, Julia; Jeong, Heisawn; Kollar, Ingo; Pellegrino, Jim

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Doing Quantitative Research in the Learning Sciences and CSCL: Current Developments and Applications

Frank Fischer (co-chair), Ludwig-Maximilians University, Munich, Germany, frank.fischer@psy.lmu.de
Freydis Vogel (co-chair), University of Hamburg, Germany, freydis.vogel@uni-hamburg.de
Daniel Bodemer, University of Duisburg-Essen, Germany, bodemer@uni-due.de
Olga Chernikova, Ludwig-Maximilians University, Munich, Germany, o.chernikova@psy.lmu.de
Ulrike Cress, Leibniz-Institut für Wissesmedien, Germany, u.cress@iwm-tuebingen.de
Bram De Wever, Ghent University, Belgium, bram.dewever@ugent.be
Julia Eberle, Ruhr-University Bochum, Germany, julia.eberle@rub.de
Heisawn Jeong, Hallym University, South Korea, heis@hallym.ac.kr
Ingo Kollar, Augsburg University, Germany, ingo.kollar@phil.uni-augsburg.de
Jim Pellegrino, University of Illinois Chicago, USA, pellegjw@uic.edu
Peter Reimann, The University of Sydney, Australia peter.reimann@sydney.edu.au
Carolyn Rosé, Carnegie Mellon University, USA, cprose@cs.cmu.edu
Nikol Rummel, Ruhr-University Bochum, Germany, nikol.rummel@rub.de
David Williamson Shaffer, University of Wisconsin-Madison, USA, dws@education.wisc.edu
Matthias Stadler, Ludwig-Maximilians University, Munich, Germany, matthias.stadler@lmu.de
Jan-Willem Strijbos, University of Groningen, the Netherlands, j.w.strijbos@rug.nl
Armin Weinberger, Saarland University, Germany, a.weinberger@edutech.uni-saarland.de
Jianwei Zhang, University at Albany, USA, jzhang1@albany.edu

Abstract: While quantitative methods are continuously developed in various fields of origin, such as psychology, the specific applications in the core field of learning sciences and CSCL are less well advanced. In this workshop, we explore and discuss current methodological topics in three relevant fields of empirical research: (1) obtaining data, (2) analyzing data, and (3) sharing data, replicating and integrating findings. Outcomes of the discussions are planned to be published in short guidelines facilitating the application of latest developments in quantitative methods in the learning sciences and CSCL research.

To what extent are recent developments in quantitative research methods relevant for the learning sciences and CSCL?

The main goal of this workshop is to both highlight the relevance of recent developments in quantitative methods to the learning sciences (LS) and CSCL community and discuss possible guidelines for applying them. There is a considerable number of researchers in the LS and CSCL community who aim at testing hypotheses derived from theories for generalizability using quantitative methods; in addition, there is an increasing number of researchers using quantifying methods to explore the relationship between constructs and variables (e.g., from the learning process) to discover new phenomena and candidates for their explanation.

In recent years, there have been methodological developments and focus shifts in several disciplines of origin such as psychology or educational science. We claim that in the LS/CSCL community we have not been striving for advancing the foundations of these types of methodologies. If at all, we mostly rely on advances in other fields and selectively apply and combine these advances to the phenomena of interest in the LS/CSCL. Yet, for researchers who may locate themselves in the learning sciences as their core discipline, there is not much information and discussion available about the applications of these methodologies.

We believe that it is important that we discuss to what extent the methodological developments and shifts in related disciplines are relevant for the research in the learning sciences and CSCL as well. For this, we will specify developments and shifts relevant to LS/CSCL research, discuss their applicability, and eventually make the new developments available to the learning sciences community. The topics are grouped into three important themes in empirical research, (1) obtaining data, (2) analyzing data, and (3) sharing data, replicating and integrating findings.

Some recent development and shifts in quantitative research methodologies

I. Obtaining data

(1) Issues with underpowered studies in the learning sciences and CSCL

One of the most pressing issues in terms of reliability of research is that many of our studies are underpowered. It is more likely to discover fancy effects in small samples. Especially in testing interaction effects of e.g., types of scaffolding and learner characteristics, studies in the learning sciences often start with a low probability of discovering an effect if it exists (a priori power) as interaction effects are typically (much) smaller than main effects. Considering the potential statistical dependency of observations made on learners in a group we probably need to think of (much) bigger sample sizes for typical CSCL studies as well. Guiding question for this issue will be: How can we raise the standards regarding rational a priori power analyses in research in the learning sciences and CSCL? How can bigger sample sizes be realized given the constraints of conducting studies in this field? What would be possible alternatives?

(2) Increasing interest in person-centered approaches

Most quantitative studies in educational and psychological research are variable-centered and aim at identifying general regularities across participants, or nomothetic relationships. Acknowledging the high diversity in mental structures and processes there has been a shift in focus to more idiographic research helping to understand how structures and processes are related and developing within one individual. With high quantities of longitudinal data on several variables, models are calculated for individuals instead of samples. More recently, there have been attempts to combine idiographic and nomothetic approaches, e.g. in latent transition analysis (Schlatter et al., 2021) or GIMME (Luo et al., 2022). A guiding question for the workshop is, whether and how quantitative idiographic approaches can be applied in CSCL and learning sciences research, and how they can be combined with nomothetical approaches.

(3) Advances in "measurement" theory

Very little of the work in the learning sciences makes use of constructs and methods from the world of educational measurement. First, traditional measurement theories have improved and new approaches to establish validity and reliability for measurements could advance the LS/CSCL field. We discuss the relevance of the idea of valid evidence and how we can draw from the psychometric and statistical fields with respect to establishing the validity of the instruments and data sources we use in evaluating hypotheses about the impact of our designs and interventions. Second, there is an increasing interest in conceptualizing measures of interest as complex and formative constructs with an emphasis on breadth of coverage. This is in stark contrast to the so far predominantly used reflective constructs with different items measuring one latent construct. If we adopt this view we need, for example, to give up on our beloved Cronbach's alpha value as a quality indicator of our measurement (Stadler et al., 2021). A guiding question for this issue would be: Are constructs related to knowledge, learning and collaboration used in LS and CSCL research more appropriately conceptualized and measured as formative constructs?

II. Analysing data

(4) Unclear roles and relationship of more traditional quantitative methods and methods from machine learning/learning analytics

At a first glance, the more traditional methods seem to have their strengths in testing hypotheses whereas machine learning based methods are strong in generating new hypotheses. However, there have been efforts to integrate machine learning approaches into highly developed traditional methods like exploratory factor analysis (Goretzko & Bühner, 2022). A guiding question for the workshop will be: What are the roles traditional quantitative methods, as well as methods from machine learning/ learning analytics can play in order to achieve the dual objective of discovering new patterns, and testing hypotheses? One specific example in this respect is how process mining techniques (see e.g. Bannert et al., 2014) can be used in studying collaborative learning scenarios.

(5) Bayesian testing. In other fields, we see an increasing number of research papers testing their hypotheses using Bayesian instead of frequentist methodologies

An advantage of Bayesian over frequentist testing is that we can quantify and evaluate the evidence for the null hypothesis (no difference) using Bayesian testing (e.g., Kelter, 2021). What are potential fields of application, and under which conditions would Bayesian testing be problematic in the learning sciences and CSCL research?

(6) Complexity and interdependence of data. In LS/CSCL research we are faced with complexity of data at multiple dimensions

The dependency of inter-individual data and group data is a particular challenge for analyzing data in CSCL research. Methods have been further developed to analyze data obtained at multiple levels. Yet, LS and CSCL research still rarely makes use of multilevel analyses (see for instance Cress, 2008). Beyond the possible use of multilevel analyses, research and measures needs to be carefully designed, level and dependency of data considered when obtaining and analyzing them. While recent developments seem to be applicable to methodological issues emerging in CSCL research, mostly the methods are not ready to use, and trade-offs need to be carefully considered when applying them. This calls for further development of methodology to better serve the needs when tackling research questions in CSCL, like e.g. addressing temporal aspects in processes of learning and interaction processes. Moreover, CSCL builds strongly on multi-modal process data and there is yet no established approach to integrating multiple sources of, e.g., discourse and physiological time series data (Aoyama Lawrence & Weinberger, 2022). Guiding questions for this topic would be: What are recent methodological developments that can be applied to better analyze CSCL process data on multiple levels and modalities?

(7) A productive relationship of quantitative and qualitative methods in research in learning sciences and CSCL

Quantitative data analyses in the learning sciences and CSCL can be combined in different ways with qualitative analyses. Maybe, the learning sciences is even developing a signature blend of these two approaches (see also Strijbos & Dingyloudi, 2018, on mixed methods). How should these combinations be designed and applied to address the complexity of questions we are addressing in the learning sciences and CSCL research?

III. Sharing data, replicating and integrating findings

(8) Replicability and reproducibility of research

The open science movement received a lot of attention in psychology, biology and medicine by showing that some of the seminal empirical studies do not replicate (e.g., Nossek et al., 2022). We do not yet know how we are doing with respect to replicability indices in LS/CSCL research and the current number of published replications in our journals is pretty low. Another issue is the operationalization of central constructs, especially when the constructs are derived from complex data that require the use of coding or rating schemes. Well-known instruments that fulfill certain standards and are widely used to ensure valid accumulation of knowledge are rarely used in our field. A promising way for increasing replicability is via fostering reproducibility by testing whether and to what extent different research groups using data and code/syntax of a study arrive at the same results and similar conclusions as the workgroup that initially designed the study and collected the data. Some of the guiding questions for the workshop are: How can we test and eventually facilitate reproducibility in quantitative research in the learning sciences and CSCL? Can we conduct multi-site studies to replicate some of the core studies in the learning sciences and CSCL? How we can establish practices to promote the reuse and general acceptance of certain instruments and replication studies to increase validity of the knowledge we produce? To what extent do replicability and reproducibility have implications for qualitative analyses of processes that many of us use in learning sciences and CSCL?

(9) Open data, FAIR, and research data management.

As sharing and letting others re-using our data is becoming standard practice in other fields (e.g., Higman et al., 2019) the number of shared data sets in the learning sciences and CSCL has yet been very low. While the community seems very open to doing so, the complexity and multi-modality of data as well as the combination of strongly connected quantitative and qualitative data in our field is a huge challenge. Managing all the different types of data in a way that is can even be reused a few years later by the researchers involved in the project is complicated and common tools and guidelines for data management are still lacking. Consequently, handing over data to others for reanalysis is even more complicated. Guiding questions are: What models are currently used for individual data management that could also promote sharing data? How can we facilitate that data of published studies is appropriately shared? How can we facilitate the re-use of the shared data by other research groups?

(10) Meta-analytic methods

With increasing numbers of empirical studies, meta-analytic approaches become more and more popular in CSCL (e.g., Jeong et al., 2019) and the learning sciences (e.g., Gerard et al., 2015). In educational research the standards for meta-analyses have recently been changing, e.g., with respect to the selection process of studies to be included, to the methods of analysis, and to the reporting on meta-analyses. What are some important implications for doing

meta-analytic research in LS/CSCL (e.g., the need to integrate findings from both, qualitative and quantitative studies)? What are limitations of these types of studies for LS/CSCL research?

Further topics

There are other timely and important topics, for instance, how we address causality and the role of experimental designs in the learning sciences and CSCL research, or the *measurement of competences in large-scale assessment* studies, where the learning sciences and CSCL communities have not been as influential as they could be. Also, *computational modeling* as a methodology widely used in neighboring fields has rarely been explored and discussed with respect to its relevance and limitations in learning sciences and CSCL research. More topics might be suggested by other workshop participants. Therefore, the preliminary structure with 10 topics assigned to three phases of research may be re-arranged in preparation of the workshop.

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