Original Article

Transforming paradigms: problematic practices and innovative approaches

Rik Crutzen
Maastricht University, The Netherlands
Gjalt-Jorn Peters
Open University of the Netherlands, The Netherlands
Olga Perski
University of California, USA & Tampere University, Finland
Szilvia Zörgő
Maastricht University, The Netherlands
Annick De Paepe
Ghent University, Belgium

The dominant approaches in health psychology have remained stagnant for decades (Chevance et al., 2021). Quantitative studies often employ variations on linear models, rarely questioning underlying assumptions and their implications. Qualitative studies, too, have seen little methodological progress, often applying a variation of coding the data in hierarchical code structures and describing the identified patterns. This methodological stagnation ultimately hinders scientific progress (Cartwright, 2021). This was the point of departure for a symposium we organized at the 37th Annual Conference of the European Health Psychology Society in Bremen, Germany. In that symposium, we addressed a selection of problematic practices in health psychology research and introduced a number of innovative approaches that hold the potential to transform paradigms and stimulate methodological and theoretical innovation.

The aim of this article is twofold. First, to provide a brief overview of the content of our symposium. Next to the slides being publicly available (Crutzen et al., 2023), this contributes to the legacy of the symposium beyond the conference. Second, to provide those interested with more details on and links to tools in order to put these innovative approaches into practice.

The regression trap

The first contribution focused on explaining why regression analyses, despite being commonly used for this purpose, are not suitable for selecting determinants to target in behavior change interventions (Crutzen & Peters, 2023). The meaning of regression coefficients is commonly explained as expressing the association between a determinant and a target behavior 'holding all other predictors constant.' As there is ubiquitous overlap between determinants, this often boils down to 'neglecting a part of the psyche.' This is because overlap manifests in correlations between determinants, which distorts the interpretation of regression coefficients. In practice, this results in interventions targeting determinants that are less relevant and, thereby, have less impact on behavior change. In earlier work, we have described Confidence Interval-Based Estimation of Relevance (CIBER) as an innovative approach to select determinants and circumvent the regression trap (Crutzen et al., 2017). The R package 'behaviorchange' contains two functions ('CIBER' and 'binaryCIBER') to apply this approach. While this approach is used (e.g., Vervoort et al., 2020), it does not solve two common problems in determinant studies. First, not being able to draw causal conclusions concerning determinants. This problem, however, cannot be solved during analyses, but needs to be addressed during study design (see fifth contribution). Second, only under very strict conditions, which are hardly obtained in psychological processes, can a generalization be made from a structure of interindividual variation to the analogous structure of intraindividual variation (Molenaar, 2004). Hence, it is warranted to focus more on within-person effects in longitudinal models of change (see third contribution).

Knowing what we're talking about

Where the first contribution discussed the problems plaguing the typical application of a common statistical technique, the second contribution dove a bit deeper and addressed more fundamental issues. Starting from psychology's replication crisis, the measurement crisis and then theory crisis were identified as underlying causes, manifesting in the jingle-jangle jungle at the construct definition level as well the measurement level. A lack of conceptual clarification is at the core of both, and the exceedingly brief construct definitions that are common in (health) psychology inevitably require researchers to elaborate definitions before being able to study those constructs. However, the elaborated versions typically remain unshared. This results in substantial hidden heterogeneity in construct definitions as they actually inform our research (and interventions). This heterogeneity in itself is desirable and contributes to scientific progress - but its hidden nature is very problematic.

Hence, a conceptual tool to facilitate explication of construct definitions: Decentralized Construct Taxonomies (DCTs; see Peters & Crutzen, 2024) was introduced that can make heterogeneity visible. A DCT is specified with a construct definition as well as corresponding instructions that prescribe how to measure the construct (for primary quantitative research), how to classify existing measurement instruments as measuring the construct (for evidence syntheses), how to code qualitative data as pertaining to the construct, and how to elicit qualitative data. This conceptual tool was implemented in a series of technical tools. These consist of a psychological construct repository, PsyCoRe.one; a mechanism for designating a Unique Construct Identifier (a UCID) to a DCT specification; and a way to enable efficient reference to the construct by appending the identifier to a URL, similar to how DOIs operate (e.g.https://psycore.one/expAttitude_expectation_73dnt5z1). Through their unique identifiers, these DCT specifications lend themselves to easy adaptation or re-use, thereby facilitating epistemic iteration (i.e. alternating innovations in theory and measurement). Finally, a number of approaches to developing such DCT specifications were discussed.

The role of formal, dynamical systems modeling in improving the precision of health psychology theories

The third contribution zoomed in on the theory crisis specifically and suggested a path forwards. Arguably, psychology's theory crisis is fuelled by two key issues: the dominance of narrative theories (i.e., verbal descriptions of explanatory frameworks for when and why psychological phenomena of interest arise; Guest & Martin, 2021) and the overreliance on between-group, static (i.e., atemporal), and linear effects modeling to study health psychology phenomena of interest (Chevance et al., 2021). Such narrative theories typically beg more questions than they can help answer and a growing body of evidence – e.g., from studies harnessing repeated, technology-enabled measurements in people's daily lives – indicates that many of the phenomena that are of central interest to health psychologists (e.g., health behaviors) are dynamically fluctuating over time in a non-linear fashion, and that these patterns look different for different individuals (i.e., they are idiosyncratic; Chevance et al., 2021).

Formal, dynamical systems modeling was introduced as a method capable of addressing both of these issues. Formal modeling involves the translation of a theory's structure into a series of mathematical equations or other types of formalism (e.g., propositional logic, agent rules). Typically, computer simulations are used to check the model's adequacy (e.g., "Can the model produce the phenomena of interest and if so, under what assumptions?") before fitting the model to real-world data. The addition of a dynamical systems lens to the formal modeling process is arguably necessary for tackling the second issue above. An overview of the Theory Construction Methodology (Borsboom et al., 2021) was provided as a guiding framework for how to apply these methods in practice (going from abstract to more concrete steps), along with an example of the steps taken to develop a formal, dynamical systems model of lapse incidence in smokers attempting to stop as part of project 'COMPLAPSE' (https://www.olgaperski.com/research/complapse). Since formal modeling is relatively new to health psychologists, a scoping review is currently in progress, which aims to summarize the methodological steps taken by researchers when formalizing health psychology theories (Perski et al., 2023). This will be used to propose a set of 'best practice' recommendations for researchers interested in applying formal modeling in their future work.

Taking time into account in qualitative research

The fourth contribution took the same critical perspective and extended it to qualitative research. Qualitative research, like quantitative research, typically only interrogates atemporal patterns in codes. This precludes studying processes unfolding over time (such as psychological processes), whereas ideally, methods leverage within-case analyses effectively, and offer procedures for aggregation over multiple research units as required. Qualitative/Unified Exploration of State Transitions (QUEST) is such a tool, visualizing Markovian models of transitions between states or steps in a process that are encoded in the data. Markovian models visualize the probability of a unit of analysis transitioning from one state to another, which can be computed for a single participant or a group. Computations for QUEST are based on a state transition network where frequencies of transitions from a state to itself and other states constitute the total transition counts for each state. Then, an adjacency matrix is created for every unit of analysis (e.g., participant) and aggregated across units (e.g., summed). This cumulative, asymmetric matrix is then parsed by a network visualizer, where nodes represent states, and edges transition probabilities. QUEST visualizes transition probabilities between unique pairs of states (e.g., from State A to State B), making it a potent tool in discovering patterns within data (Zörg et al., 2023). Aggregation across units (e.g., multiple participants) raises interesting questions about combining idiosyncratic representations of state transitions, such as what exactly the aggregate represents and in which instances such aggregation is meaningful. QUEST is a novel piece of functionality within the R package {rock}, which implements the Reproducible Open Coding Kit (ROCK), a standard for working with qualitative data (Zörg & Peters, 2023). The package {rock} and more information about the standard, including step-by-step guides on employing the R package, can be found at https://rock.science, and a tutorial for QUEST will be available at https://rock.science/posts/2023-09-quest.html.

Embracing causal thinking

The fifth contribution argued that the main aim of research within the field of health psychology is to inform policies and practices to alter people's behavior. Knowledge about the factors that are causally affecting behavior are therefore crucial. Randomized Controlled Trials are considered the gold standard to infer causality, but often they are unethical or unfeasible to conduct. As a result, we need to turn to quasi-experimental or observational studies. Early on in our scientific training we learn that we cannot draw causal conclusions from these designs and we therefore avoid using causal language. Nevertheless, we still often (implicitly) draw causal conclusions (e.g. by making recommendations for policy). Refraining from causal language and more importantly causal thinking is potentially harmful and may lead to biased results and wrong conclusions, because the methods used to estimate causal effects are not the same as those used to estimate associations (Hernán, 2018).

Directed Acyclic Graphs (DAGs) provide the necessary tools for articulating the assumptions on which causal interpretations of statistical associations rely and provide a clear basis for constructive discussion among researchers. DAGs are schematic representations, developed based on domain knowledge, about the hypothesized causal relationships between the involved variables and can be used to identify confounders, mediators and colliders (Greenland et al., 1999; Pearl, 2009). Although DAGs are increasingly used by epidemiologists, they remain relatively rare within applied health sciences (Tennant et al., 2021). Lack of knowledge of how to best develop DAGs has been suggested as one of the main reasons the uptake of DAGs is limited (Barnard-Mayers et al., 2021). Recently, we conducted a scoping review in which we aimed to provide an overview of the guidelines and recommendations for developing DAGs (Poppe et al., submitted). Based on this overview we created six guiding steps to consider when creating a DAG: (1) start as early as possible (ideally before designing the study); (2) clearly specify your research question (with clear construct definitions for your exposure and outcome, see second contribution); (3) add common causes (or confounders); (4) consider taking selection bias into account; (5) consider taking measurement bias into account; (6) use DAGs to inform your study design and data-analysis. A useful tool to start creating your own DAG is 'dagitty', that can be used in a browser-based environment (https://www.dagitty.net) as well as with an R package (Textor et al., 2016). Once you have created a DAG it is highly recommended to include it in your paper, so that you are transparent about your assumptions.

In sum, although methodological stagnation was the point of departure, the symposium was hopeful in paving the way for scientific progress. With this article, we hope to contribute to furnishing health psychology with the conceptual and operational tools to establish this progress.

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Rik Crutzen
Maastricht University, The Netherlands
rik.crutzen@maastrichtuniversity.nl

Gjalt-Jorn Peters
Open University of the Netherlands
gjalt-jorn@behaviorchange.eu

Olga Perski
University of California, San Diego & Tampere University, Finland
olga.perski@tuni.fi

Szilvia Zörgő
Maastricht University, The Netherlands
s.zorgo@maastrichtuniversity.nl

Annick Lena De Paepe
Ghent University, Belgium
annick.depaepe@ugent.be