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Use of measurement theory for operationalization and quantification of psychological constructs in systems dynamics modelling

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Abstract. The analytical tools available to social scientists have traditionally been adapted from tools originally designed for analysis of natural science phenomena. This article discusses the applicability of systems dynamics – a qualitative based modelling approach, as a possible analysis and simulation tool that bridges the gap between social and natural sciences. After a brief overview of the systems dynamics modelling methodology, the advantages as well as limiting factors of systems dynamics to the potential applications in the field of social sciences and human interactions are discussed. The issues arise with regards to operationalization and quantification of latent constructs at the simulation building stage of the systems dynamics methodology and measurement theory is proposed as a ready and waiting solution to the problem of dynamic model calibration, with a view of improving simulation model reliability and validity and encouraging the development of standardised, modular system dynamics models that can be used in social science research.

1. Introduction

The analysis tools available to social scientists have traditionally been developed to study and analyse physical phenomena and have been designed to meet the requirements of disciplines, which gather ratio or interval data such as physics and engineering. These tools have subsequently been adapted for application to the softer human oriented sciences such as psychology and education. Due to the different measurement approaches adopted by social scientists, who predominantly gather ordinal or nominal data, the tools are routinely applied to data without checking that it meets the assumptions required by a particular method and these issues have attracted some attention [1]. A few techniques have been developed specifically to handle qualitative concepts and these include: qualitative reasoning [2], soft systems methodology [3], causal mapping and systems dynamics [4]. These powerful qualitative approaches allow researchers to create dynamic models able to cope with uncertainty and incomplete information through the use of latent constructs as the main unit of analysis. Not only does this allow for a flexible and relatively easy structuring of the modelled event but the approach enables direct and intuitive interpretation of the results [2].

A particular advantage of the qualitative approaches mentioned above is the use of feedback loops to represent the dependence and complex interrelations between variables as a process that develops over time, rather than a static snapshot of the system at just one point in time. This representation naturally fits in with social science phenomena which consist of a number of components from different phenomenological domains (sensory, behavioural, attitudinal) that interact and it is these interactions within a particular time frame, coupled with the structural dependence between the



components, that give rise to a range of possible outcomes [5]. However, the dynamic nature of social phenomena has been generally ignored by social science researchers who traditionally take a reductionist approach in their studies [5] by considering as static snapshot of the system and just one particular point of time.

A notable attempt to move away from the reductionist approach is the work by development psychologist Esther Thelen [6] who adopted a Dynamic System Theory (DST) approach to her studies. Dynamic system theory evolved from classical mechanical engineering and uses sets of differential or difference equations to model the interactions between system variables over time and the system's output is determined by a mixture of past inputs and the output changes over time if the system is not in a state of equilibrium [7]. The dynamic systems approach was designed to handle problems from exact sciences and its approach is still predominantly reductionist as the objective is to build a mathematical model of the system whose behaviour can be examined under different initial conditions, although it has the capacity to handle feedback by using classic control theory tools.

An alternative methodology, developed in the mid 1950s by Jay Forrester for modelling analysing social science problems is system dynamics [4]. The objectives of system dynamics are: "... studying and managing complex feedback systems, in managerial, organizational and socioeconomic context..." [7, p. 5] and this is achieved by a set of simple rules for representing interrelationships between latent and observable variables to model complex dynamical entities. The system dynamics modelling methodology as identified by Sterman [8] is carried out in seven steps: the first step identifies a problem of interest to the researcher by specifying the endogenous and exogenous variables to be included in the model, followed by the statement of a tentative dynamic hypotheses that make a tentative assumption about the causes of the problem to be addressed. The researcher then builds a representation of the dynamic system using causal loop diagrams (CLD), which are used to examine the interrelationship between the different variables in the system. The interaction between different types of feedback loops, positive and balancing as well as inherent delays in the system give rise to a range of different behaviours, such as exponential growth, s-curve and oscillation, that can be exhibited by the system. The causal loop diagrams are then converted into a computer simulation using stocks and flows, which can be used to simulate a range of different scenarios in order to identify the best solution to the problem. The modelling methodology's final step is the implementation of the identified optimal strategy into practice.

System dynamics provides a natural and easy way to identify relationships between variables at the causal loop diagram stage by describing the sign of the correlation/association between two variables, rather than specifying the magnitude of the relationship. So if two variables are positively correlated an increase in one variable will result in an increase in the other, whereas negative relationships will be reflected by an increase in one variable, leading to a decrease in the other (all else being equal), however, the rates of change will not be specified at this stage of the modelling process. For example, as shown by Lizeo [9] in considering the impact of student willingness for working in groups on the group performance, we can describe the interrelationship between four of the variables in the system (willingness to work in groups, number group activities, performance and complacency) as follows: As the students willingness to work in groups increases, so would the number of learning oriented activities they undertake, which in turn will increase the group performance. As group performance increases, we can expect that this will also in turn increase the willingness to work in a group. This will be a positive loop (see Figure 1). However, as students' performance increases, the group complacency will also increase and as complacency increases, this will in turn lead to fewer learning oriented activities, leading to a decrease in performance. Complacency forms part of a negative feedback loop. So the performance of the group will be determined by the interaction of the positive loop of willingness to work and the negative loop of group complacency. The actual behaviour observed at any on point in time will depend on the initial conditions for the group, i.e. their complacency and willingness to work in a group. So it is to be expected that a group with high complacency and low willingness to work will perform less well (all other factors being equal) than a

group with high willingness to work and low complacency, even though this analysis is carried out without reference to specific values.

This qualitative analysis is a useful tool for identifying drivers of group's performance, but in order to maximise the utility of the model, a dynamic simulation can be developed, quantifying the constructs used in the qualitative analysis. However, converting the causal loop diagrams to a dynamic simulation model poses two major challenges for the researcher, namely: operationalization of any latent constructs into variables and quantification of the measurement variables.

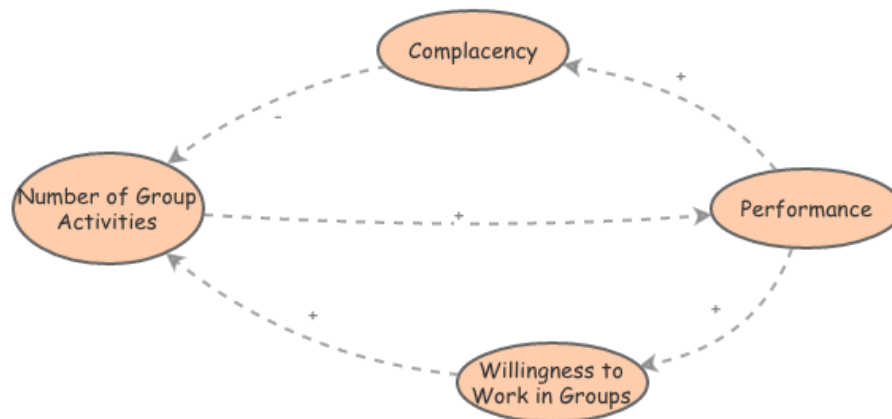


Figure 1. Causal loop diagram of factors affecting group performance

2. Challenges with dynamic simulation building

2.1. Operationalization of latent constructs.

The first issue arises as a result of the inherent difficulties of operationalizing latent scales and converting them to meaningful variables [10]. Latent constructs form an important part of psychological investigations and are used widely as tools for building frameworks representing the dimensions of latent concepts. The process is well established and involves the use of observable or manifest variables, gathered using questionnaires, and factor analysis to ascertain the underlying structure of the latent construct by identifying the manifest variables that load highly on each dimension. This is inherently a constructivist approach as it assumes that knowledge about unknown concepts is inferred from known entities (namely manifest variables) [11]. While intuitively appealing, doubts have been raised regarding the suitability of psychometric tests as a tool for operationalizing latent constructs under the positivist phenomenological umbrella as they violate the assumption of logical independence between the observed and unobservable entities [11]. Operationalizing latent constructs during the causal loop diagram stage of the systems dynamics methodology is relatively easy as systems dynamics was designed with the objective of handling easily both latent and observed variables. For example, the causal loop diagram in Figure 1 linked effortlessly the impact of complacency and group performance and allow researchers to use the variables in order to identify systemic and structural dependences in the system. However, moving onto the simulation stage of the systems dynamics methodology poses some challenges as performance is an observable variable which can be operationalized relatively easily by considering the assignment grade or the average grades for the students to date, for example, while complacency is not that easy to operationalize. The difficulties arise at a number of points in the process of converting a concept into a simulation variable, starting from the nominal definition of the concept, through to its quantification [10].

The first step of defining a latent simulation variable requires clear statements of its nominal definition, although this is not always explicitly stated in the systems dynamics methodology. Nominal definitions, normally developed by lexicographers, can encompass different aspects of the

same concept. For instance, the definition of complacency in the Cambridge Online Dictionary is: “a feeling of calm satisfaction with your own abilities or situation that prevents you from trying harder” whereas the Merriam-Webster dictionary defines complacency as: “a feeling of being satisfied with how things are and not wanting to try to make them better”. Although similar in defining complacency as a feeling, the two nominal definitions are not identical. The first definition suggests a necessity for calmness and is focused on the self and trying harder, while the second takes on an exogenous focus on making things better. Each definition places emphasis on a different aspect of the feeling and any operationalization of the variable will reflect the inherent assumptions taken by the researcher. Although nominal definitions are outside the remit of system dynamics, the system dynamics methodology requires researchers to be explicit about the variables included in any particular model as part of the first stage of the model building process, leading to greater transparency of the inherent assumptions made at that stage.

A further issue that affects operationalization of latent variables at the simulation stage of the systems dynamics methodology is that of generalizability. Social scientists are well aware of the multidimensional nature of latent constructs and routinely use factor analysis to build reliable and valid scales for measuring latent constructs. However, the majority of scale developed are context specific as that reduces their dimensionality and improves their reliability [12], [13]. Context-specificity ties in closely with the problem oriented nature of system dynamics but it also feeds into one of its inherent weaknesses as it encourages creation of models that are specific to the problem at hand, rather than more generic system models that could be used in a range of different contexts [7]. In a similar vein in social sciences reliability and validity are the main drivers in determining the suitability of measurement instruments such as latent constructs but the quest for improving reliability and validity also pushes researchers into greater and greater context-specificity, which in turn affects the generalizability of the research conclusions. However, while the issue of model validation has received relatively little attention in the field of systems dynamics [14], the debate of validity in the field of psychology has been on going [15], [16]. Unified approaches for testing model validity by using a network of argument based claims that can be build up to any level of complexity have been proposed [16] and this approach may offer a systematic framework for testing the validity of systems dynamics models, although some doubts have been raised with regards to the widely adopted nomological approach to validity [15]. A different approach to validity, defining it as a variation of the attitude leading to a causal variation in the measured outcome have also been proposed [15], and offer a more flexible alternative to the traditional nomological network of constructs. There seems to be further scope for developing reliability and validity measures that take into account the context-specificity of the developed model and impose a penalty for any model that is too context specific. This could be similar to the Bayesian Information Criterion for example, which tests the goodness of fit of quantitative models to the data used to build them but also imposes a penalty for loss of degrees of freedom which occurs as the number of estimated parameters and complexity of the mathematical models increases [17]. A corresponding measure in social sciences will encourage the creation of less context specific models and encourage social scientists to focus on generalizability.

2.2. *Quantification of latent constructs*

The second issue that a researchers face when building a system dynamics simulation is that of quantification of the latent variables [18]. The issue arises as psychological measurements are normally gathered using multidimensional instruments with nominal or ordinal scales. However a systems dynamics simulation assumes that the variables simulated are interval or ratio since their values are added, subtracted and multiplied as part of the modelling process [19]. The problem is compounded further by the fact that different latent variables could be measured on different scales. Therefore, the two aspects that need to be addressed in quantification of variables for the system dynamic simulation are:

- Converting variables’ scale of measurement into one meeting the criteria of (at least) interval scale measurements.

- Defining appropriate methodologies for combining constructs with different scales with the objective of building meaningful composite measures.

Measurement theory provides the means for addressing these issues. Significant strides have been made into the development of person and item invariant measurement scales using models proposed by Guttman, Rasch and Mokken [20]. These item and person invariant scales can be combined and linked without loss of generalizability [21] and Rasch models can be used as a confirmatory tools to verify that ordinal data gathered using Likert-type scale questionnaires satisfy the equidistance constraints of interval data. The interval data can be converted into ratio scale by appropriate modification such as the one suggested by Levine [18].

Research into linking different scales using non-parametric approaches and achieving meaningful composite measures for latent variables is also on going in other disciplines such a clinical studies [22] and further development in this area can be expected as a result of growing interest in the development of meta analytic analysis tools [23]. Therefore, the research carried out in measurement theory can help overcome the limitations of systems dynamics by providing a robust set of tools for quantifying and operationalizing latent constructs and converting them into observable, ratio scale variables that can be used in dynamic simulations.

Although some researchers have questioned the assumption that “true” measurement and quantification of latent constructs is possible due to the heterogeneous nature of the intervals between the different measurement categories gathered using Likert scales [11], [24], a particular advantage of system dynamics models is their capacity to accurately represent the structural dependence of the entities within the system, without any a priori assumptions of the specific measures of the modelled variables. By focusing on the behaviour of variables over time, rather than at a particular instance in time, researchers can draw generalised conclusions about the variable behaviour. Thus system dynamics models offer an alternative structure driven analytical approach which can overcome some of the objections raised to the use of latent variables in traditional data driven analytical approaches [11].

3. Conclusion

This article examined the applicability of systems dynamics as a possible analysis and simulation tool that bridges the gap between social and natural sciences. A brief overview of the systems dynamics modelling methodology identified causal loop diagrams as a powerful tool for identifying system behavior generated by the structural dependence between the different entities, providing social scientist with an intuitive and easy to use analytical instrument. However, the simulation stage of the system dynamics methodology identified challenges with the operationalization and quantification of latent variables and measurement theory was proposed as a solution to the problem of dynamic model calibration. Of particular note are approaches for building invariant scales, which can be used to create meaningful and accurate composite measure variables that satisfy the criteria for ratio type measurement. The use of standardized variables and measurement will facilitate the development of standardized, modular system dynamics models that can be used by social scientists for model validation and in theory design.

References:

- [1] J. M. Batista-Foguet, B. Ferrer-Rosell, R. Serlavós, G. Coenders, and R. E. Boyatzis, “An Alternative Approach to Analyze Ipsative Data. Revisiting Experiential Learning Theory,” *Front. Psychol.*, vol. 6, pp. 575–10, Nov. 2015.
- [2] L. Travé-Massuyès, L. Ironi, and P. Dague, “Mathematical Foundations of Qualitative Reasoning.,” *AIM*, vol. 24, no. 4, pp. 91–106, 2004.
- [3] P. B. Checkland, *Systems Thinking, Systems Practice*. John Wiley & Sons Ltd., 1998.
- [4] J. W. Forrester, “System dynamics—a personal view of the first fifty years,” *Syst. Dyn. Rev.*, vol. 23, no. 2, pp. 345–358, Oct. 2010.
- [5] S. Salvatore, W. Tschacher, O. C. G. Gelo, and S. C. Koch, “Editorial: Dynamic systems

- theory and embodiment in psychotherapy research. A new look at process and outcome,” *Front. Psychol.*, vol. 6, pp. 1–3, Jul. 2015.
- [6] E. Thelen, “Dynamic systems theory and the complexity of change,” *Psychoanal Dialogues*, vol. 15, no. 2, pp. 255–283, 2005.
- [7] L. Osipenko and J. Farr, “System Dynamics and Dynamic Systems Integration in Regulatory Environments,” presented at the System Dynamics Society Conference, Oxford, 2004.
- [8] J. D. Sterman, *Business Dynamics: Systems Thinking and Modeling for a Complex World*. McGraw-Hill, 2000.
- [9] E. Lizeo, “A dynamic model of group learning and effectiveness,” presented at the System Dynamics Society Conference, Boston, 2005.
- [10] C. Jacobsen and R. Bronson, “Defining sociological concepts as variables for system dynamics modeling,” *Syst. Dyn. Rev.*, vol. 3, no. 1, pp. 1–7, Dec. 1987.
- [11] J. Michell, “Constructs, inferences, and mental measurement,” *New Ideas Psychol.*, vol. 31, no. 1, pp. 13–21, Apr. 2013.
- [12] C. Robie, M. J. Schmit, A. M. Ryan, and M. J. Zickar, “Effects of Item Context Specificity on the Measurement Equivalence of a Personality Inventory,” *Organ Res Methods*, vol. 3, no. 4, pp. 348–365, Oct. 2000.
- [13] M. Kunter, A. Frenzel, G. Nagy, J. Baumert, and R. Pekrun, “Teacher enthusiasm: Dimensionality and context specificity,” *Contemp Educ Psychol*, vol. 36, no. 4, pp. 289–301, Oct. 2011.
- [14] Y. Barlas, “Formal aspects of model validity and validation in system dynamics,” *Syst. Dyn. Rev.*, vol. 12, no. 3, pp. 183–210, Sep. 1996.
- [15] D. Borsboom, G. J. Mellenbergh, and J. van Heerden, “The Concept of Validity,” *Psychol Rev*, vol. 111, no. 4, pp. 1061–1071, 2004.
- [16] M. T. Kane, “The argument-based approach to validation,” *School Psych Rev*, 2013.
- [17] J. J. Dziak, D. L. Coffman, S. T. Lanza, and R. Li, “Sensitivity and specificity of information criteria,” Penn State University, 12-119, 2012.
- [18] R. L. Levine, “System dynamics applied to psychological and social problems,” presented at the System Dynamics Society Conference, Bergen, Norway, 2000.
- [19] C. Nuthmann, “Using human judgment in system dynamics models of social systems,” *Syst. Dyn. Rev.*, vol. 10, no. 1, pp. 1–27, Mar. 1994.
- [20] G. Engelhard Jr., “Historical Perspectives on Invariant Measurement: Guttman, Rasch, and Mokken,” *Measurement (Mahwah N.J)*, vol. 6, no. 3, pp. 155–189, Aug. 2008.
- [21] W. P. Fisher, “Invariant thinking vs. invariant measurement,” *RMT*, vol. 14, no. 4, pp. 778–781, 2001.
- [22] K. M. Wittkowski, E. Lee, R. Nussbaum, F. N. Chamian, and J. G. Krueger, “Combining several ordinal measures in clinical studies,” *Statist. Med.*, vol. 23, no. 10, pp. 1579–1592, May 2004.
- [23] I. K. Crombie and H. T. Davies, “What is meta-analysis,” *What is*, 2009.
- [24] D. Borsboom, G. J. Mellenbergh, and J. van Heerden, “The theoretical status of latent variables,” *Psychol Rev*, vol. 110, no. 2, pp. 203–219, 2003.