



# Contrasting roles of measurement knowledge systems in confounding or creating sustainable change

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## ABSTRACT

Sustainable change initiatives are often short-circuited by failures in modelling. Unexamined assumptions about measurement and numbers push modelling into the background as a presupposition rarely articulated as an explicit operation. Even when models of system dynamics are planned components of a sustainable change effort, the key role of measurement is typically overlooked. The crux of the matter concerns the distinction between numeric counts and measured quantities. Mistaking the former for the latter confuses levels of complexity and fundamentally compromises communications. Reconceiving measurement as modelling multilevel distributed decision processes offers new alternatives aligned with historically successful efforts in creating sustainable change. Five conditions for successful sustainable change are contrasted from the perspectives of single-level vs multilevel modelling: vision, plans, skills, resources, and incentives. Omitting any one of these from efforts at creating change result, respectively, in confusion, treadmills, anxiety, frustration, and resistance. The shortcomings of typically implemented single-level approaches to measurement result in the widespread experience of these negative consequences. Results show that new potentials for creating sustainable change can be expected to follow from implementations of multilevel distributed decision processes that effectively counteract organizational amnesia by embedding new learning in an externally materialized knowledge infrastructure incorporating a shared cultural memory.

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## 1. INTRODUCTION

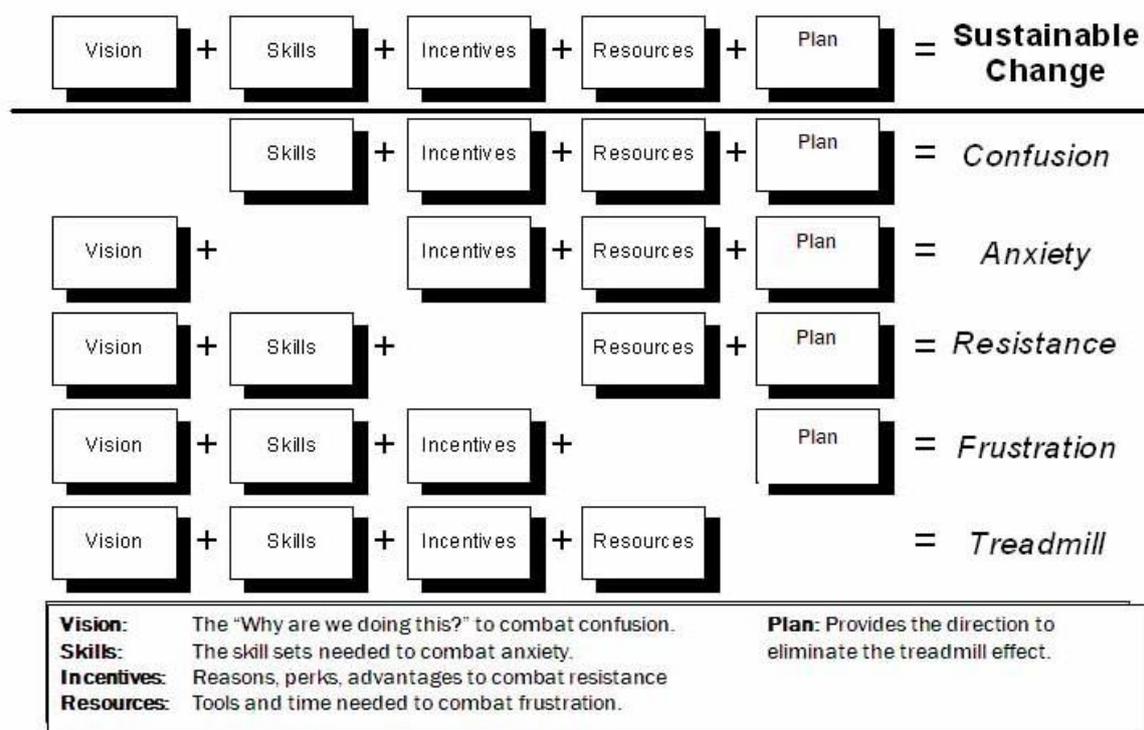
A little known but landmark article [1] defines five conditions for success in creating sustainable systems change (Figure 1). Different approaches to meeting these conditions can produce results that vary dramatically in their sustainability. Of particular importance is the measurement knowledge infrastructure context in which the five conditions are deployed.

Systems change initiatives in organizations ranging from schools to hospitals to private firms typically make use of information on processes, structures, and outcomes obtained from tests, assessments, or surveys of students, patients, employees, customers, suppliers, and other key stakeholders. This information can be aggregated and reported in markedly different ways, with associated variation in its meaningfulness, utility, and consequences for success in creating sustainable change.

The primary points of contrast between opposing poles of information quality can be summarized in terms of two approaches to measurement. On one end of this quality continuum are models lacking distinctions between discontinuous levels of complexity, and at the other end are models addressing these levels in ways that facilitate their practical management. The polar opposites come to the fore in oft-repeated but rarely heeded contrasts between statistical analyses of ordinal data and scientific models of interval units.

These contrasts emphasize differences between unexamined assumptions about causal relationships and the meaningfulness of ordinal scores, on the one hand, and, on the other, intentional requirements of meaningful interval unit definitions [2]-[9]. Where the former focuses on the concrete terms of objective facts, the latter instead focuses on the abstract and formal terms of objectively reproducible unit quantities. The statistical focus on ordinal scores manages what counts in relation to accountability reporting systems, assuming the whole is the sum

# Conditions for Successful Implementation



Knoster, T., Villa, R., & Thousand, J. (2000)

Figure 1. Conditions for sustainable change [1]

of the parts. The scientific focus on interval quantities manages what adds up in relation to the overall mission, requiring the whole to be more than the sum of the parts.

The end results of the statistical focus on ordinal scores for sustainable change involve a kind of myopia unable to focus beyond the limits of local circumstances to global concerns [10]. A systematic literature review of almost 300 articles on lean thinking practices in health care, for instance, found that "tool-myopic thinking tends to be a prevalent practice and often governs implementations" [11]. The tendency here is to not be able to see the forest for the trees.

Measurement is commonly defined as the assignment of numbers to observations according to a rule. Decades of criticism as to the insufficiency of this definition [2]-[9] can be traced back to Whitehead's 1925 fallacy of misplaced concreteness [12]. Parallel demonstrations of superior definitions of measurement dating from the 1960s have had little impact on practice [13], [14].

Measurement is usually, then, deemed achieved by means of ordinal, nonlinear score models irrevocably attached to the specific questions asked, with no experimental test of causal hypotheses and no uncertainty estimates. Scientific approaches instead fit data to models of interval and linear measurements whose meanings are demonstrably independent of the specific questions asked, are contextualized by tested causal hypotheses and uncertainties, and are deployed in networks of quality-assured instruments distributed throughout multilevel networks of end users [15]-[17].

Contrasts between these paradigmatically opposed approaches to quantification (see Table 1) illuminate new potentials for creating sustainable change. When the differences

between statistical and scientific measurement modelling approaches are grasped, today's organizational cultures can be seen as having counterproductively adapted to accepting as inevitable failure to meet the conditions for successful implementation of sustainable change. In other words, because of the widespread but unexamined assumption that low quality measurement information is the best that can be expected, confusion, feeling caught on a repetitive treadmill, anxiety, frustration, and resistance are built into organizational cultures in often unnoticed but pervasive ways.

Organizational amnesia [18], [19] of this kind can, however, be counteracted by scientific measurement modelling approaches that retain learning and incorporate it organically into scaffolding built into the external environment as a kind of cultural memory. Research into learning embodied and locally situated in the institutional environment [20]-[22] points toward new goals organizations can realistically set for achieving sustainable change using scientific measurement models instead of statistical data models.

## 2. TYPICAL STATISTICAL MODELLING

### 2.1. Vision

Visualizing the future requires anticipation of highly abstract arrays of possible scenarios. The kinds of challenges that might be encountered must be conceived in conjunction with the kinds of responses needed to address them. All too often, however, vision statements focus so narrowly and myopically on local concrete circumstances [10], [11] that long-term planning, staffing, resourcing, and incentivizing are inadvertently sabotaged.

Table 1. Statistical vs Scientific Modelling Paradigm Contrasts vis a vis Sustainable Change Conditions.

Sustainable Change Condition	Statistical Modelling Paradigm	Scientific Modelling Paradigm
Vision	Centralized gathering and analysis of ordinal instrument-dependent data for policy formation	Distributed network of instruments traceable to common units informs and aligns end user decisions and behaviours
Skills	Item writing & administration, response scoring, statistical summarization, reporting	Construct definition and modelling, instrument calibration, item banking, adaptive end user application
Incentives	Rewards for perceived goal attainment	Shared success in general improvements to organizational viability
Resources	Investments limited as not accountable for or expected to produce significant returns	Investments proportional to magnitudes of returns from improved efficiencies and market share
Plan	Interprets ordinal scores as interval and all numeric differences as meaningful; no context for improvement provided	Scales interval measures with individual uncertainty and data quality estimates; quantitative continuum qualitatively annotated to guide change efforts
Implications for managing what is measured	Management focuses on moving numbers that matter within restricted domain of limited observations, sometimes at expense of mission	Management focuses adaptively on relevant tasks representing mission, skipping tasks irrelevant to challenges of the moment
Implications for communication	Ordinal scores interpreted as interval tied to limited number of particular items results in obscure and difficult comparisons	Interval measures interpreted relative to entire bank of calibrated items opens up clear and transparent opportunities for learning

The usual vision informing reasons why measurements are made is to gather data for analysis and summarization in reports to be used in formulating policy directives. Even if this vision is informed by Design Thinking [23], [24], and so incorporates the elements of empathy, definition, ideation, prototyping, and testing, the focus on scores (counts and/or percentages of correct answers, or of responses in a rating category) unnecessarily limits what can be imagined and accomplished to a small fraction of the available potential [25].

That is, the restricted orientation to responses to specific questions necessarily prevents the envisioning and realization of goals that would otherwise be achievable. This is because a vision limited to statistical treatments of ordinal scores does not meaningfully model or map the substantive features of the situation of interest. The map is not the territory. Mapping proceeds from concrete observations of what is happening on the ground but must aspire to represent those concrete features by identifying coherent patterns at abstract and formal levels of higher order complexity.

Because real world circumstances are in constant flux, meaningful and useful maps cannot remain tied to any single given set of conditions. A general continuum defining a learning progression, developmental sequence, or healing trajectory must characterize the quantitative range of variation [26]-[27]. An abstract perspective is the only way to adaptively and resiliently inform individuals and groups about where they are located

relative to where they were, where they want to go, and what comes next, no matter what concrete circumstances they find themselves in.

The narrow vision associated with statistically modelled ordinal scores mistakes mere numbers for quantities and pays a high price for doing so. Comparability depends on all respondents answering the same questions, and standards are imagined as necessitating use of the same indicators. The resulting knowledge infrastructure is envisioned on the basis of information quality that cannot support generalized meaning, and so vision is obscured, and confusion results.

## 2.2. Planning

Applications of the information obtained from scores, ratings, and percentage statistics usually focus on generalizations that assume all numeric differences of a given magnitude mean the same thing, though this assumption is usually not, and likely cannot be, substantiated. The inferential problems following from this unwarranted assumption of uniform meaning are then further compounded by the ways the scores are interpreted and applied. With no information typically made available on the uncertainty ranges or confidence intervals associated with the scores, there is no way of telling if and when numeric differences are real and reproducible, or are simply random noise.

In addition, because questions are each treated separately, as domains unto themselves, no information on a learning progression, developmental sequence, healing trajectory, or other quality improvement continuum is made available. Improvement efforts then can do nothing but focus directly on areas in which failure (low ratings or incorrect answers) is experienced, instead of first ensuring that prerequisite foundations for sustainable change have been put in place. The result of acting on this kind of low-quality statistical information is then to continue repeating the same pattern of efforts in precisely the endless treadmill cycle one wanted to avoid.

## 2.3. Skills

The skills required in commonly adopted statistical approaches to measurement focus on knowledge of the relevant content and processes involved for assessment and survey development, social interactions for administering those tools, operational awareness for policy formation, and data input, aggregation, analysis, and reporting. Analyses may be as simple as counting correct answers or responses within rating categories, and computing percentages, or as complex as any advanced statistical method may be.

The focus of data analytic skills unjustifiably presumes without evidence that results will retain their meaning across levels of complexity. But the statistical skills employed in usual approaches to measurement mistreat concrete scores as abstract quantities explained by formal theory, when they are not. That is, everyone is well aware that it is impossible to tell from my count of ten rocks whether I have more or less rock than someone with two rocks. It is also common knowledge that correct responses to ten questions cannot be understood as indicating more ability or success than correct responses to two questions, since the two groups of questions asked may vary markedly in difficulty. Statistical modelling proceeds by focusing on these merely numeric data anyway, mistakenly assuming that nothing better can be done. Failure to bring the needed skills to bear can only then result in anxiety, since the information produced is readily seen to be disconnected from the circumstances in which it is supposed to be applied.

## 2.4. Resources

Resources invested in the statistical modelling approach to creating sustainable change are typically focused on minimizing expenditures in producing a one-time snapshot of the state of things used for setting policy going forward. No specific forms of returns are expected, so the investments made are not usually accountable except as expenses, which are kept to the lowest possible levels. The information produced is typically used only as a conspicuously displayed expression of the fact that attention is being focused in some way on matters of concern to an interested party. But with vision, skill sets, and plans limited to low quality ordinal scores whose meanings are tied to the particular questions asked, the structural limits imposed on potential returns means only limited investments of resources can be justified and the usual result is a frustrating inability to advance.

## 2.5. Incentives

In the context of the usual approach to statistical data modelling, incentives are usually cast in relation to achieving results defined in terms of counts, scores, or percentages. Student proficiency scores or patient/customer/employee satisfaction or performance ratings are interpreted as evidence of achievements that are then rewarded by recognition, bonuses, promotions, etc. But because the data are tied to responses to specific questions, and because they are moreover ordinal, nonlinear, and not mapped to variation in meaningful amounts of a measured construct, incentive systems like this are easily gamed. Even without the advantages of a perspective informed by scientific measurement, this general management problem is recognized as leading to confusion, conflict, inefficiency, and a lack of focus [28].

In education, for instance, having students memorize tasks known to be included in the items on a test can inflate scores without, however, actually improving proficiency. In more extreme cases, teachers and principals have conspired to change student test scores. Similarly, customer satisfaction surveys are often accompanied with requests for ratings at a specific level or higher. The explicit goal is to create an appearance of success that can be rewarded in a public way that conveys an atmosphere of positive progress and overcomes resistance, even when the substantive failure to change anything is readily apparent to everyone involved. Because the vision, skills, and incentives are all focused on specific and discrete concrete issues that can never adequately represent the abstract and formal levels of complexity, unfair biases serving some agendas and undermining others will likely promote resistance of some form or another as the usual consequence.

## 3. INNOVATIVE SCIENTIFIC MODELLING

### 3.1. Vision

An alternative vision as to why measurements are made focuses on modelling a decision process, calibrating instruments informing that process, distributing those instruments to front line decision makers, and gathering data for periodic analysis and summarization in reports used for quality improvement and accountability. This vision makes clear provisions for creating knowledge systems offering practical value beyond periodically produced reports. When the demands of effective knowledge infrastructures [21], [25], [29], [30] are met, data are reported at each level of complexity relevant to the demands of end users.

Front line managers like teachers, clinicians, and others engaged in individualized care processes need denotative facts contextualized within learning progressions, developmental sequences, disease natural histories, etc. Practice management requires metalinguistic statistical summaries of interval logits reported to facilitate communication and comparability over time and space, within and across individuals, classrooms, clinics, schools, hospitals, etc. Accountability requires metacommunicative theoretical explanatory power that justifies decision processes at the metalinguistic and denotative levels. To the extent this is accomplished, one might reasonably expect less confusion to be produced than is commonly associated with the statistical approach.

### 3.2. Planning

Applications of the information obtained from scientifically modelled measurements require experimental tests substantiating the requirement that numeric differences of a given magnitude mean the same thing, within the range of estimated uncertainty. Measurements are interpreted and applied in relation to uncertainty ranges or confidence intervals, which makes it possible to tell if and when numeric differences are real and reproducible, or are simply random noise. In addition, because questions are scaled together to delineate a learning progression, developmental sequence, or quality improvement trajectory, measurements are interpreted substantively in relation to the amount of the construct represented at each scale level.

Improvement efforts then can focus attention on the easiest tasks not yet accomplished. Now a foundation for sustainable change has been put in place by successes experienced at lower levels of difficulty. The result is that end users' behaviours and decisions are coordinated and aligned by their shared responses to the same information. When end users can, in addition, easily learn from one another by sharing knowledge, probabilities of breaking free of treadmill cycles are increased.

### 3.3. Skills

The skills required for implementing scientific models of decision processes are considerably more technically and socially sophisticated than the skills associated with the usual statistical data modelling approach. All of the latter's skill sets are needed, as well as mastery of advanced conceptual tools involving construct mapping, assessment/survey item development, response scoring, mathematical model formulation, instrument calibration; measure, uncertainty, and data quality interpretation; knowledge system development, administrative and interpretation guidelines, user training, etc. These skills focus on producing knowledge retaining its meaning and properties across levels of complexity, suggesting the possibility of resulting in less anxiety than has been the case in using the statistical approach.

### 3.4. Resources

With experience, resources invested in the scientific modelling approach to creating sustainable change can be gauged for maximizing returns from ongoing improvements in efficiency and outcomes. As expectations concerning returns take shape, lessons are learned as to how the investments can be made accountable. With a vision, skill sets, and plans aimed at maximizing the value of high-quality interval measurements whose meanings are independent of the particular questions asked, investments proportionate to the expected returns can be justified, and the business plan can be scaled up as the market expands.

### 3.5. Incentives

In the context of scientifically modelling an overall decision process, incentives are shaped by involving everyone as participants in the creation of enhanced processes and outcomes. The overarching viability of the organization is placed front and centre. Incentives reward generalizable innovations that improve quality. Given common languages of comparison, everyone has the information they need to take responsibility for the outcomes in their care. Inputs that do not positively impact qualitatively and/or quantitatively measurable affective, cognitive, behavioural, etc. outcomes can be evaluated for removal.

In the traditional statistical modelling approach, the maxim "you manage what you measure" becomes a cynical motto conveying how management can be distracted into superficial issues only peripherally related to the main operational focus of the organization. In the scientific modelling context, though, managing what is measured is akin to turning a wrench fitted on the head of a bolt that needs to be tightened: the tool is fit for purpose. The distribution of instruments calibrated to a common metric informs decision processes and data sharing that everyone can learn from quickly and easily. Incentives overcome resistance, then, by illuminating clear paths to forward advances increasing the pride everyone takes in their work.

## 4. DISCUSSION

Scientific modelling is superior to statistical modelling in the context of promoting sustainable change because, first, it provides a vision that encompasses the entire populations both of potential challenges that may emerge and of potential participants (employees, students, teachers, clinicians, suppliers, managers, etc.) who may engage with those challenges. This capacity follows from the focus of scientific models on the abstract construct represented in measurements, as opposed to the concrete data and specific questions focused on by statistical models. The usual statistical approach accepts ratings and scores as meaningful, even though their significance depends on the particular questions that were asked. So when challenges not represented in the questions and associated data emerge, those challenges are likely to be ignored, discounted, or distracting in ways that lead to confusion. Scientific models, in contrast, inform clarity by demanding a theoretical account supported by data and expressed in comparable metrics with known uncertainties.

Second, scientific modelling dispels anxiety by bringing advanced expertise to bear on problem definition, construct mapping, instrument calibration, report generation, measure interpretation, and quality improvement applications. Though statistical modelling skill sets may, of course, be highly developed, many change initiatives are approached with little more experience than familiarity with spreadsheets and word processors. Though these latter rudimentary methods are commonly used, the importance of communicating meaningful results in well-defined terms will likely continue to exert an inexorable demand for higher quality knowledge.

Third, because scientific modelling supports new degrees of rigorous comparability over time, new expectations for accountability and accounting can be expected to alter the quality and quantity of resistance-countering incentives that can be offered. Proportionate returns on investment will follow from fair and equitable measurements that are demonstrably reproducible and relevant to the challenges to innovation being faced. These kinds of returns should become the goal of change efforts, instead of incentive systems that can be gamed, creating

the appearance of innovation by focusing on easily counted signal events, with the associated demoralizing atmosphere that goes with widely perceived unfair advantages.

Fourth, in the same vein, because the magnitudes of impacts are commonly estimated in the confusing terms of statistical scores, the resources brought to bear in change efforts are commonly insufficient to effect significant results, leading to continued frustration. The capacity to generalize and scale across contexts by means of a combination of explanatory theory, experimental evidence, and distributed instrumentation, however, leads to the clear definition of opportunities for investment likely to pay handsome returns.

Fifth, where the statistical focus on improvement planning is typically guided by nothing more than the areas of failure or low ratings, the scientific approach maps the improvement trajectory. This is done in a way that more closely informs day to day activities by indicating where a process is at relative to its goal, and showing what comes next in a logical sequence. Instead of simply taking on the most difficult challenges with no attention to preparatory factors, the scientific approach attends to establishing baseline structures, processes, and outcomes in an orderly approach.

Differences in circumstance across situations can be accommodated via adaptive selection of relevant tasks and challenges, without compromising overall comparability. This results in a visible documentation of small gains as progress toward the goal is made, as opposed to the feeling of being on a treadmill that results from not being oriented on a clear path toward defined goals.

## 5. CONCLUSION

Successful sustainable change initiatives depend on abilities to flexibly and quickly store and retrieve knowledge. Centralized repositories of low-quality information accessed infrequently are likely to result in muddled vision, inconsequential skill sets, ineffective incentives, insufficient resources, and incomplete plans. Distributed networks of instruments embodying high quality information, in contrast, offer the potential for counteracting the confusion, anxiety, resistance, frustration, and treadmills too commonly taken for granted.

## REFERENCES

- [1] T. P. Knoster, R. A. Villa, J. S. Thousand, A framework for thinking about systems change, In R. A. Villa & J. S. Thousand (Eds.), *Restructuring for Caring and Effective Education*, Brookes, Baltimore, 2000, pp. 93-128.
- [2] D. Andrich, Distinctions between assumptions and requirements in measurement in the social sciences, In J. A. Keats, R. Taft, R. A. Heath & S. H. Lovibond (Eds.), *Mathematical and Theoretical Systems*, Elsevier Science Publishers, 1989.
- [3] J. Cohen, The earth is round ( $p < 0.05$ ), *American Psychologist*, 49 (1994), p. 997-1003. Online [Accessed 19 December 2022] <https://psycnet.apa.org/record/1995-12080-001>
- [4] O. D. Duncan, M. Stenbeck, M. Panels and cohorts, In C. C. Clogg (Ed.), *Sociological Methodology 1988*, American Sociological Association, New York, 1988, pp. 1-35.
- [5] W. P. Fisher, Jr., Statistics and measurement: Clarifying the differences, *Rasch Measurement Transactions*, 23 (2010), pp. 1229-1230. Online [Accessed 19 December 2022] <http://www.rasch.org/rmt/rmt234.pdf>
- [6] P. E. Meehl, Theory-testing in psychology and physics: A methodological paradox, *Philosophy of Science*, 34 (1967), pp. 103-115. DOI: [10.1086/288135](https://doi.org/10.1086/288135)

- [7] J. Michell, Measurement scales and statistics: A clash of paradigms, *Psychological Bulletin*, 100 (1986), pp. 398-407.  
DOI: [10.1037/0033-2909.100.3.398](https://doi.org/10.1037/0033-2909.100.3.398)
- [8] D. Rogosa, Casual [sic] models do not support scientific conclusions: A comment in support of Freedman, *Journal of Educational Statistics*, 12 (1987), pp. 185-95.  
DOI: [10.3102/10769986012002185](https://doi.org/10.3102/10769986012002185)
- [9] M. Wilson, Seeking a balance between the statistical and scientific elements in psychometrics, *Psychometrika*, 78 (2013), pp. 211-236.  
DOI: [10.1007/s11336-013-9327-3](https://doi.org/10.1007/s11336-013-9327-3)
- [10] T. Hopper, Stop accounting myopia: think globally: A polemic, *Journal of Accounting & Organizational Change*, 15 (2019), pp. 87-99.  
DOI: [10.1108/JAOC-12-2017-0115](https://doi.org/10.1108/JAOC-12-2017-0115)
- [11] A. Akmal, R. Greatbanks, J. Foote, Lean thinking in healthcare, *Health Policy*, 124 (2020), pp. 615-627.  
DOI: [10.1016/j.healthpol.2020.04.008](https://doi.org/10.1016/j.healthpol.2020.04.008)
- [12] A. N. Whitehead, *Science and the modern world*, Macmillan, New York, 1925.
- [13] R. D. Luce, J. W. Tukey, Simultaneous conjoint measurement, *Journal of Mathematical Psychology*, 1 (1964), pp. 1-27.  
DOI: [10.1016/0022-2496\(64\)90015-X](https://doi.org/10.1016/0022-2496(64)90015-X)
- [14] G. Rasch, *Probabilistic models*, Danmarks Paedagogiske Institut, Copenhagen, 1960.
- [15] W. P. Fisher, Jr., Invariance and traceability for measures of human, social, and natural capital. *Measurement*, 42 (2009), pp. 1278-1287.  
DOI: [10.1016/j.measurement.2009.03.014](https://doi.org/10.1016/j.measurement.2009.03.014)
- [16] L. Pendrill, *Quality assured measurement*, Springer, Cham, 2019 ISBN 978-3-030-28695-8.
- [17] L. Mari, M. Wilson, A. Maul, *Measurement across the sciences*, Springer, Cham, 2021 ISBN 978-3-030-65558-7.
- [18] R. Othman, N. A. Hashim, Typologizing organizational amnesia, *The Learning Organization*, 11 (2004), pp. 273-284.  
DOI: [10.1108/09696470410533021](https://doi.org/10.1108/09696470410533021)
- [19] C. Pollitt, *Institutional amnesia*, Prometheus, 18 (2000), pp. 5-16.  
DOI: [10.1080/08109020050000627](https://doi.org/10.1080/08109020050000627)
- [20] E. Hutchins, The cultural ecosystem of human cognition, *Philosophical Psychology*, 27 (2014), pp. 34-49.  
DOI: [10.1080/09515089.2013.830548](https://doi.org/10.1080/09515089.2013.830548)
- [21] S. L. Star, K. Ruhleder, Steps toward an ecology of infrastructure, *Information Systems Research*, 7 (1996), pp. 111-134.  
DOI: [10.1287/isre.7.1.111](https://doi.org/10.1287/isre.7.1.111)
- [22] J. Sutton, C. B. Harris, P. G. Keil, A. J. Barnier, The psychology of memory, extended cognition, and socially distributed remembering, *Phenomenology and the Cognitive Sciences*, 9 (2010), pp. 521-560.  
DOI: [10.1007/s11097-010-9182-y](https://doi.org/10.1007/s11097-010-9182-y)
- [23] H. Plattner, C. Meinel, L. Leifer (Eds.), *Design Thinking Research: Measuring Performance in Context*, Springer Science & Business Media, Cham, 2012.
- [24] A. Royalty, B. Roth, Mapping and Measuring Applications of Design Thinking in Organizations, In *Design Thinking Research* (pp. 35-47), Springer International Publishing, Cham, 2016. ISBN 978-3-030-76324-4
- [25] W. P. Fisher, Jr., E. P.-T. Oon, S. Benson, Rethinking the role of educational assessment in classroom communities, *Educational Design Research*, 5 (2021), pp. 1-33.  
DOI: [10.15460/eder.5.1.1537](https://doi.org/10.15460/eder.5.1.1537)
- [26] W. P. Fisher, Jr., Imagining education tailored to assessment as, for, and of learning, *Assessment and Learning*, 2 (2013), pp. 6-22. Online [Accessed 19 December 2022]  
[https://www.researchgate.net/profile/William-Fisher-Jr/publication/259286688\\_Imagining\\_education\\_tailored\\_to\\_assessment\\_as\\_for\\_and\\_of\\_learning\\_theory\\_standards\\_and\\_quality\\_improvement/links/5df56a2592851c83647e7860/Imagining-education-tailored-to-assessment-as-for-and-of-learning-theory-standards-and-quality-improvement.pdf](https://www.researchgate.net/profile/William-Fisher-Jr/publication/259286688_Imagining_education_tailored_to_assessment_as_for_and_of_learning_theory_standards_and_quality_improvement/links/5df56a2592851c83647e7860/Imagining-education-tailored-to-assessment-as-for-and-of-learning-theory-standards-and-quality-improvement.pdf)
- [27] P. Black, M. Wilson, S. Yao, Road maps for learning, *Measurement: Interdisciplinary Research and Perspectives*, 9 (2011), pp. 1-52.  
DOI: [10.1080/15366367.2011.591654](https://doi.org/10.1080/15366367.2011.591654)
- [28] M. C. Jensen, Value maximization, stakeholder theory, and the corporate objective function, *Journal of Applied Corporate Finance*, 22 (2010), pp. 32-42.  
DOI: [10.1111/j.1745-6622.2010.00259.x](https://doi.org/10.1111/j.1745-6622.2010.00259.x)
- [29] W. P. Fisher, Jr., Contextualizing sustainable development metric standards, *Sustainability*, 12 (2020), pp. 1-22.  
DOI: [10.3390/su12229661](https://doi.org/10.3390/su12229661)
- [30] W. P. Fisher, Jr., Bateson and Wright on number and quantity, *Symmetry*, 13 (2021) 1415.  
DOI: [10.3390/sym13081415](https://doi.org/10.3390/sym13081415)