Misconceived relationships between logical positivism and quantitative research

Chong Ho Yu, Ph.D.

Paper presented at the Annual Meeting of

the 2001 American Educational Research Association, Seattle, WA

Published in *Research Method Forum*, 2003

http://www.aom.pace.edu/rmd/2002forum.html

Revised on July 18, 2005

Forthcoming in the book *Philosophical foundations of quantitative research methodology*

as a chapter (Laham, MD: University Press of America)

Correspondence:

Chong Ho Yu, Ph.D.

PO Box 612

Tempe AZ 85280

Email: chonghoyu@yahoo.com

Website: http://www.creative-wisdom.com/pub/pub.html

**Abstract**

Although quantitative research methodology is widely applied by social scientists, there is a common misconception that quantitative research is based upon logical positivism. This misconception leads to misguided disputes between qualitative and quantitative researchers. This article points out that the polarities between the two are unnecessary, and the richness and continuity of “research traditions” is therefore proposed as a replacement for the incommensurability in the Kuhnian “paradigm.” Further, this article examines the relationship between quantitative research and eight major notions of logical positivism: (a) verification, (b) pro-observation, (c) anti-cause, (d) downplaying explanation, (e) anti-theoretical entities, (f) anti-metaphysics, (g) logical analysis and (h) frequentist probability. It is argued that the underlying philosophy of modern quantitative research does not subscribe to logical positivism. Associating an outdated philosophy with quantitative research may discourage social science researchers from applying this research approach. Researchers and students should be encouraged to keep an open mind to different methodologies because mixed methods have the potential to achieve the goals of convergent validity and completeness.

# Misconceived relationships between logical positivism and quantitative research

## Introduction

Feldman (1998) observed that while positivism has been universally rejected by philosophers of science over the past fifty years, current textbooks still either associate quantitative methods with positivist ones or cover quantitative methods within a positivist frame of reference. Despite the fact that newer epistemologies and methodologies, such as post-positivism, critical realism, and critical multiplism, have been discussed in numerous books and articles (Cook, 1985, 1991, 1993; Cook & Campbell, 1979; Cook & Shadish, 1994; Phillips, 1987, 1990a, 1990b, 1992, 2000; Phillips & Burbules, 2000), the debate regarding the paradigm of quantitative methods seems to be trapped in a time warp.

The objectives of this paper are threefold. First, I argue that the dichotomy between the two approaches is misguided due to the popular notion of "paradigm" introduced by Kuhn, which tends to polarize methodological differences and thus leads to epistemological incommensurability. Instead, the problem would be reframed under the notion of "research tradition" advocated by Laudan. Second, historical and theoretical evidence is cited in attempt to break the philosophical ties between quantitative methodology and logical positivism. Logical positivism, which rejects theoretical constructs and causality and emphasizes reductionism, is too restrictive to apply to quantitative methodology, which supports the use of latent constructs, causal inferences, and the iterative process of undestanding the data and developing constructs. Last, I argue that when quantitative research departs from logical positivism and methodological differences/similarities are re-conceptualized in research tradition, it widens the door to triangulation with the goals of convergence and completeness.

## Misconceptions of quantitative research

The misconceived relationships between positivism and quantitative research can still be found in recent textbooks. For example, Berg (2001) explicitly identified quantitative research as a positivistic approach: "Positivists utilize empirical methodologies borrowed from the natural sciences to investigate phenomena. Quantitative strategies serve this positive-science ideal by providing rigorous, reliable, and verifiably large aggregates of data and the statistical testing of empirical hypotheses” (p.10). Merriam (1998) also related certain “positivist” characteristics to quantitative methods:

> In positivist form of research…knowledge gained through scientific and experimental research is objective and quantifiable…on the topic dropping out of high school…From a positivist perspective you might begin by hypothesizing that students drop out of high school because of low self-esteem. You could then design an intervention program to raise the self-esteem of students at risk. You set up an experiment controlling for as many variables as possible, and then measure the results. (p. 4)

Further, in many texts comparing qualitative and quantitative research, the attributes of the latter are often misidentified. The following are some examples: particularistic (quantitative) vs. holistic (qualitative) emphasis, outcome-oriented (quantitative) vs. process-oriented (qualitative), fixed (quantitative) vs. emergent (qualitative) categories, static (quantitative) vs. fluid (qualitative) reality (Huysamen, 1997), mechanical (quantitative) vs. creative (qualitative), formulaic (quantitative) vs. interpretive (qualitative) (Howe, 1988), expansionist (qualitative) vs. reductionist (quantitative), and grounded (qualitative) vs. ungrounded (quantitative) (Reichardt & Cook, 1979).

These comparisons are grounded in the misunderstood relationship between quantitative research and the positivist/logical positivist paradigms. For example, qualitative researchers use the grounded theory (Glaser & Strauss, 1967) to develop “categories” that could fit the data until the categories are saturated. The process is said to be an iterative abstraction grounded on the data. In a similar vein, quantitative researchers employ exploratory factor analysis to develop latent constructs until all dimensions emerge and all observed variables can be properly loaded into the abstracted dimensions. It is difficult to see why the former is said to be grounded while the latter is ungrounded. Probably, this misunderstanding is due to the association between the one-way reductionism endorsed by certain logical positivists and quantitative methods. Further, the perception that quantitative research assumes static reality is attributable to the myth that logical positivists are realists. The notion that quantitative researchers are confined by fixed categories results from the omission of the fact that quantitative researchers utilize open concepts and customized instruments in different contexts. In a later section this article will fully discuss the core ideas of logical positivism and point out that the preceding perceived connection is mistaken.

## Research tradition vs. Paradigm

One of the sources of the misunderstanding can be traced back to the oversimplification of quantitative research. Usually quantitative research is viewed as Fisherian hypothesis testing, and various statistical procedures are regarded as a unitary approach that can be summarized in a single paradigm. However, at the ontological, epistemological, and methodological levels, the Fisherian school, the Neyman/Pearson school, the Bayesian school, the resampling school, and the exploratory data analysis (EDA) school are fundamentally different, and to some extent are incompatible (Lehmann, 1993; Berger, 2001; Behrens, 1997; Behrens & Yu, 2003). Further, in the arena of measurement, the classical test theory and the item response theory are also very different in their premises and assumptions (Embretson & Reise, 2000). According to Kuhn (1962), following a paradigm, all members of a specific scientific community accept a set of commonly agreed exemplars. However, it is doubtful whether the Kuhnian paradigm theory could be applied to such a rich collection of epistemologies and methodologies in quantitative research. Laudan (1977) argued that the paradigm theory does not fit with the history of science. Indeed, it is not uncommon for a number of competing theories based upon incompatible exemplars to coexist. Thus, Laudan proposed the concept of "research tradition" in an attempt to replace "paradigm."

Laudan is not alone. In reaction to the viewing of quantitative research as a positivist approach, Clark (1998) embraced the view that quantitative research is shaped by more than one philosophy. In a similar vein, Cook (1985) doubted that all social and natural scientists have subscribed to all positivist assumptions, that positivism adequately describes scientific practice as it occurs, and that this practice has evolved only from the positivist framework. Rather, Cook asserted that "scientific practice has multiple origins that include trial-and-error behavior of practitioners, selective adaptations from prior philosophies and research" (p.23). Thus, it would be an oversimplification to treat quantitative methods as a single paradigm. A more appropriate treatment of this issue is to classify different schools of quantitative methods into different research traditions.

Further, in the Kuhnian framework, paradigms are competing worldviews that would inevitably lead to **incommensurability**. Paradigms are said to be so different that in most cases researchers belonging to different camps could not find even a common language in which to conduct a meaningful comparison. Following the Kuhnian view, it is not surprising to see the polarities of “particularistic vs. holistic,” and “fixed vs. emergent,” as cited in the previous section. Very often researchers express frustrations that some concepts such as reliability and validity, which are taken for granted in the quantitative paradigm, do not have equivalent terms in the qualitative counterpart, and thus mixed methods seem to be in vain. No wonder Phillips (1988) even went so far as to assert that if researchers looked back to the origins of the quantitative and qualitative paradigms, they would never adopt mixed methods.

On the contrary, Laudan emphasized continuity, commensurability, and rationality among research traditions under the common thread of problem-solving. By reviewing the history of science, Laudan gave a detailed and in-depth analysis of how theories are weighted and decisions could be made on the ground of problem-solving effectiveness. Indeed, common threads could be observed in both qualitative and quantitative research traditions. For instance, while introducing qualitative methods, Miles and Huberman (1984) used a metaphor of detective work for illustration. A researcher’s role, in their view, is like a detective’s: “When the detective amasses fingerprints, hair samples, alibis, eyewitness accounts and the like, a case is being made that presumably fits one suspect far better than others.” (p.234) Interestingly enough, John Tukey (1977, 1980), the quantitative researcher who invented Exploratory Data Analysis, also related EDA to detective work. In Tukey’s view, the role of the EDA researcher is to explore the data in as many ways as possible until a plausible "story" of the data emerges. This common theme shared by both qualitative and quantitative researchers fits Laudan’s description of inquiry as problem solving.

When we look for differences among various research traditions, we could easily locate and polarize these differences. Nevertheless, we could also seek continuity and common ground, and conduct integration among different traditions. Take various schools of thought in quantitative methods as examples again. Despite the fact that Fisher, Pearson, and Neyman held different views of probability, their notions of null hypothesis, Alpha level, statistical power, Type I error, and Type two error were synthesized into hypothesis testing. In recent years researchers such as Berger (2000, 2001) and Pawitan (2000, 2001) have been independently devoting effort to fusing Bayesianism and Frequentism.

Laudan's notion of research traditions nonetheless reflects a more realistic picture of the history of scientific inquiry and the current status of quantitative methods. In the following discussion quantitative methodology is portrayed as a collection of different approaches; nevertheless, readers should keep in mind that certain degree of commonalities within various statistical schools still exist. By the same token, although the incompatibility between logical positivism and quantitative methods is highlighted, they still maintain certain overlapped areas, which will be discussed in the section entitled "Links between logical positivism and quantitative methods."

## Major themes of logical positivism

To examine the relationship between quantitative methods and logical positivism, one must define logical positivism. It is important to note that there are differences between classical positivism, introduced by French philosopher August Comte, and logical positivism, which originated in the Vienna Circle, which is composed of a group of European scholars centered around Vienna during the 1920s and 30s, such as M. Schlick, R. Carnap, H. Feigl, P. Frank, K. Gödel, H. Hahn, V. Kraft, O. Neurath, and F. Waismann. In the classical sense, positivism refers to a philosophy that scientific inquiry should be empirical, which led to antirealism and instrumentalism. In the Vienna Circle, besides the emphasis on empirical knowledge, the theme of logical positivism is also centered on the verifiability principle of meaning and logical analysis (Phillips, 2000). In addition, classical positivism was founded by Comte with the goal of systematization of sociology, but logical positivism covers a wide variety of philosophical topics such as philosophy of language, symbolic logic, philosophy of science, and philosophy of mathematics. Further, classical positivism is basically a single movement whereas logical positivism is the result of interactions among several movements, such as analytical philosophy, logical atomism, logical empiricism, and semantics. Table 1 highlights the differences between these two schools of thought. Please keep in mind that these are some examples and the list is by no means exhaustive.

Table 1. Differences between classical positivism and logical positivism

| | Classical positivism | Logical positivism |
|---|---|---|
| Emphasized source(s) of knowledge | empirical | Empirical and logical |
| Focus areas | sociology | Philosophy of language<br>Symbolic logic<br>Philosophy of science<br>Philosophy of mathematics |
| Development | Single movement | Analytical philosophy<br>Logical atomism<br>Logical empiricism<br>Semantics |

Werkmeister (1937a, 1937b) identified seven major theses of logical positivism based upon articles and books written by members of the Vienna Circle: (a) Knowledge is knowledge only because of its form. Content is non-essential. (b) A proposition is meaningful if only if it can be verified. (c) There is only empirical knowledge. (d) Metaphysics are meaningless. (e) All fields of inquiry are parts of a unitary science: physics. (f) The propositions of logic are tautologies. (g) Mathematics can be reduced to logic. Although Werkmeister's outline captures the essence of logical positivism promoted by the Vienna circle, later logical positivism expanded beyond this community, and some of the Vienna circle's notions are not held by many logical positivists. Moreover, (a), (e), and (f) are not directly related to quantitative methods. Thus, in this article, the definition of logical positivism is adopted from a more recent framework developed by Hacking (1983), which represents the common threads of most logical positivists. This framework will be explained in the following paragraph.

Some logical positivist notions outlined by Hacking are very similar to those of Werkmeister. According to Hacking, there are six major themes of positivism: (a) an emphasis on verification, (b) pro-observation, (c) anti-cause, (d) downplaying explanation, (e) anti-theoretical entities, and (f) anti-metaphysics. Logical positivism accepts all of the above notions and adds an emphasis on logical analysis. Today, when many authors discuss the relationship betwee positivism and research methodology, the context is situated in logical positivism rather than classical positivism. For example, Bogdan and Tayler (1975) explicitly contrasted qualitative and quantitative methodologies in the frameworks of phenomenological and logical positivist philosophies. Therefore, in this article the relationship between quantitative methods and logical positivism will be examined. Based upon the preceding notions, logical positivists developed a specific version of frequentist probability theory. Each of these issues will now be discussed individually.

Verification

To logical positivists, the verification criterion is not just a demand for evidence. Verification does not mean that, with other things being equal, a proposition that can be verified is of vastly greater significance than one that cannot. Rather, the verification thesis is much stronger and more restrictive than the above. According to logical positivism, a statement is meaningless if verification is not possible or the criteria for verification are not clear. This notion can be applied in such a radical manner that moral, aesthetic, and religious statements are considered non-verifiable and thus meaningless (Ayer, 1936; Schlick, 1959). In this sense, statements such as “peace is good,” “the painting is beautiful,” and “God loves the world” are all meaningless. The verification principle can go even further to make statistics meaningless! If the verification criterion is based on empirical evidence, mathematics, including statistics, which cannot be confirmed or disconfirmed by experience, is said to be nonsense by analytic philosopher Ayer (1946). For example, there is no empirical proof to support the claims that “An eigenvalue is the sum square of factor loadings” and “a logit is the natural log of the odd ratio.” To be specific, the verification principle is not an account of the relative importance of propositions, but a definition of meaning. Meaning and verifiability are almost interchangeable (Werkmeister, 1937a).

However, in the tradition of quantitative research, there is no evidence that any major quantitative researchers subscribe to this radical epistemology. For example, Cronbach, the famous statistician who introduced “Cronbach coefficient Alpha” and “construct validity,” did not restrict his inquiry to only verifiable materials in the logical positivist sense. When Cronbach contemplated the problem of causal inferences in research, he did not employ LISREL or other quantitative causal modeling techniques. Instead, he looked to the more qualitative methods of the ethnographer, historian, and journalist. He maintained that these methods are more practical and flexible than those of quantitative causal modeling (Cook, 1991).

Further, statistical methods do not provide verification in the logical positivistic sense. The logic of statistical hypothesis testing is not to verify whether the hypothesis is right; rather, the logic is to find the probability of obtaining the sampled data in the long run given that the null hypothesis is true. However, if we put any theory in the perspective of the “long run,” nothing can be conclusively verified. We are not able to verify whether a particular penny is a fair coin even if we observe the outcomes of trials in which the coin is tossed. No matter how many times the coin is tossed, the number of trials cannot be equated with the “long run.” To rectify the problem, Watkins (1985) framed statistical hypotheses in the Popperian falsificationist spirit (Popper, 1959, 1974). In Popper's view, conclusive verification of hypotheses is not possible, but conclusive falsification is possible within a finite sample. In addition, Popper is explicitly opposed to verificationism (Sanders, 1993). If a theory is claimed to be verified by an observed consequence, the researcher may commit the fallacy of affirming the consequent. A good example of this fallacy is that “if it rains, the floor is wet. If the floor is wet, it rains.” By the same token, it is fallacious to claim that “if the treatment is effective, the scores will increase. If the scores increase, the treatment is verified as effective.” Although the Popperian notion is controversial and probably carries certain flaws (Howson & Urbach, 1993), it has been considered by some quantitative researchers to be a replacement of the verification logic.

Pro-observation

While verificationism defines the meaning of knowledge, empirical observation is a specific methodology for verification. Schlick (1959) stated that reality refers to experience. However, Schlick (1925/1974) did not maintain that there is a direct path from sense experience to genuine knowledge because immediate contact with the given is both fleeting and subjective. Sense experience comes from particular observations or awareness with reference to a here and now, but empirical laws go beyond such experience. To logical positivists, pro-observation is concerned with empirical laws instead of raw experience (Friedman, 1991; Werkmeister, 1937b).

The debatable issue is Schlick's notion that reality is referred to experience. This notion has been inflated to be a notion that empirical observation implies one objective reality. To be specific, quantitative research is viewed by qualitative researchers as empirical research based on the ontology of an objective reality (Glesne & Peshkin, 1992).

First, pro-observation does not necessarily lead to the position of realism (Phillips & Burbules, 2000). As a matter of fact, logical positivism is viewed as a type of conventionalism, relativism, and subjectivism (Laudan, 1996). Contrary to popular belief, some logical positivists are anti-realists. Even those logical positivists who accept a realist position do not regard the aim of science as finding the objective truth corresponding to the objective reality. Instead, they view inquiry as a convention for conveniences. The most well known brand of conventionalism is Carnap's linguistic conventionalism (Carnap, 1937). From Carnap's standpoint, scientific inquiry allows more than one answer to the question of the meaningfulness of particular sentences. Knowledge claims can only be raised or answered with respect to a particular linguistic convention. Laudan (1996) warned that this relativistic attitude would hinder researchers from bringing academic disputes to a rational closure.

Phillips (1987, 2000) and Phillips and Burbules (2000) also argued that it is fantasy to view positivists as realists and the empirical method as the road to objective truth. To logical positivists, even if there is an ultimate reality, we do not have direct contact with this reality; the only thing that matters is what we are in contact with (observation/experience). Therefore, Phillips and Burbules classified logical positivists as phenomenalists and sensationalists, rather than realists. Phillips (2000) asserted that the beliefs of antirealism, relativism, and subjectivism occurring in some social science research “place them [the researchers] closer to the spirit of logical positivism than they suppose in even their wildest dream” (p.166).

Second, quantitative research methodology is not necessarily objective, let alone based on one objective reality or aimed at seeking one objective truth. The mainstream Bayesian approach is based upon subjective probability, which represents a degree of belief. Usually a Bayesian starts with an assessment of initial probability that involves some background knowledge. This prior subjective probability would be later corrected by the posterior probability based upon the observed data. According to the frequency and logical theories of probability, probability is objective in nature, and thus when there are two or more estimated probabilities, only one of them could be correct. This notion seems to support the assertion that quantitative researchers seek one objective reality. However, according to the Bayesian theory of probability, the only true probabilities are either one or zero. In a single event, the expected outcome either happened or did not happen. Prior to the event, probability is a degree of belief, and thus it is subjective. Although the iteration process may eventually lead subjective probabilities to some degree of convergence, Bayesians do not claim that they could give sound reasons to substantiate a truth-like conclusion. Rather, they just claim that there are reasons to modify one’s belief in the light of new evidence.

Anti-cause

Many educational and psychological researchers incorrectly attribute causal inferences to logical positivism. For example, Erlandson et al. (1993) asserted that "the very structure of our language (and thus our conceptual structure?) heavily depends on the traditional term of positivism…It is particularly hard to expunge from our memories such terms as causality" (p. xii). By the same token, Nation (1997) states that "one precept of logical positivism is that evidence favoring the objective existence of cause and effect can be provided" (p.68). Surprisingly, even some quantitative researchers improperly make a connection between causality and positivism. For example, Gliner and Morgan (2000) said that in the positivist's view, "every action can be explained as the result of a real cause that precedes the effect temporally" (p.21).

Actually, the opposite is true. Influenced by Hume's notion that causation is just a perceived regular association and Russell's anti-cause position, quite a few logical positivists do not pursue causal inferences in inquiry. Russell (1913) explained relationships in terms of functions. For example, Y = a + bX can be rewritten as X = (Y - a)/b. Thus, X could not be viewed as a cause of Y because the positions of X and Y could be swapped around the equation. By embracing this equation-oriented notion, Russell argued against causation:

> All philosophers imagine that causation is one of the fundamental axioms of science, yet oddly enough, in advanced sciences, the word 'cause' never occurs…The law of causality, I believe, is a relic of bygone age, surviving, like the monarchy, only because it is erroneously supposed to do no harm. (cited in Pearl, 2000, p. 337)

Pearl, the renowned computer scientist who applies causal interpretation into structural equating modeling, objects to Russell's anti-cause attitude: "Fortunately, very few physicists paid attention to Russell's enigma. They continued to write equations in the office and talk cause-effect in the cafeteria; with astonishing success they smashed the atom, invented the transistor and the laser" (p.338).

In logical positivism, the anti-cause position, the pro-observation thesis, and the anti-theoretical entities notion, which will be discussed in a later section, are inter-related. The meaning of causation has been approached by different schools of thought. One of these approaches believes that causation involves a producing or forcing phenomenon (If X is a cause of Y, a change of X produces or forces a change in Y) (Blalock, 1964). However, this view is incompatible with logical positivism's perspective that "cause," as an invisible force or a theoretical entity, cannot be observed or measured. In brief, according to verificationism, statements that can't be verified had no content. Causal statements are non-verifiable statements (Schuldenfrei, 1972).

Obviously, the anti-cause notion is contradicted by quantitative research in the context of randomization experiments, latent construct theory, structural equation modeling (Yu, 2001), and meta-analysis. In evaluating the counterfactual logic, Glymour (1986) said, “One of the principal goals of statistics has always been the determination of causal relations from both experimental and nonexperimental data” (p.966). The cause and effect relationship is still undetermined even if X occurs when Y occurs. An experienced researcher would question whether X still occurs in spite of Y or regardless of Y. This doubt would lead to a counterfactual question: What would have happened to X if Y were not present? Some researchers apply randomized experiments in attempt to answer this counterfactual question. By introducing a control group (~X), a causal inference can be asserted based upon counterfactual logic: If X is true, then Y is true. If X is not true, Y is not true. Thus, Y is said to be causally responsible for X. In addition to drawing causal inferences from randomized experiments, Cook (1991) went even further to interpret results of quasi-experiments in a causal fashion. Interestingly enough, some concepts about experimental design are explicitly related to causation. For example, “internal validity” is also known as “local molar causal validity,” and “external validity” is concerned with causal generalization (Cook, 1991, 1993).

In the latent construct theory, also known as the measurement model, the relationship between the latent factor and the observed item is considered a cause and effect relationship (Borsboom, Mellenbergh, & van Heerden, under review). Although operationalists view the latent construct as nothing more than a numeric trick to simplify the observations (condensing many observed items into one factor), Borsboom et al. assert that operationalism and the latent construct theory are fundamentally incompatible. If a latent construct is just for operational convenience, then there should be a distinct latent factor for every single test researchers construct. However, since it is assumed that observed items that are loaded into a factor constitute a single dimension, theoretical constructs are implied to be causally responsible for observed phenomena.

Factor analysis is one of the most popular applications of the latent factor theory.  Abbott (1998) argued that early psychometricians viewed factor analysis as a mathematical convenience to reduce complex data to simple forms in order to reconcile quantitative data with intuitive categories, and thus it ignored causality altogether. This view seems to be concurred by Laudan (1977). Laudan classified psychometrics in the early 20th century as a "non-standard research tradition" because it does not have a strong ontology or metaphysics. Instead, its assumption is "little more than the conviction that mental phenomena could be mathematically represented" (p.105). However, Laudan also asserted that, unlike what Thomas Kuhn described in the paradigm theory, a research tradition is hardly uniform. Rather, competing and incompatible views could coexist within the same research tradition at the same time, and the ontology and metaphysics could change drastically within the tradition over time. Indeed, it is arguable whether early psychometricians were a-causal. While discussing the origin and development of factor analysis, Vincent (1953) asserted that factor analysis is an attempt to identify the causes that are operating to produce the variance and to evaluate the contribution of each cause. In his view, the argument among early psychometricians was concerned with whether one common cause or multiple causes were appropriate. Further, modern scholars view factor analysis as an application of the principle of common cause (e.g., Glymour, 1982; Glymour, Scheines, Spirtes, & Kelly, 1987). Factor analysis has been incorporated into the structural equation model, which blatantly allows for causal inferences.

Structural equation modeling (SEM), which entails factor models and structural models, definitely specifies cause and effect relationships (Hoyle, 1995). In SEM, a factor model depicts relationships between indicators and underlying factors (Kline, 1998). Experimental design aims at strengthening causal inferences, which are weak or missing in quasi-experiments and non-experiments (Christensen, 1988; Cook & Campbell, 1979; Luker et al., 1998). Usually SEM requires a very large sample size. It is difficult, but not impossible, to recruit thousands of subjects for laboratory experimental studies. Not surprisingly, most data in SEM are observational or quasi-experimental rather than experimental. Nonetheless, Glymour, Scheines, Spirtes, and Kelly (1987) argued that causal inferences could be drawn from SEM based on non-experimental data. Because after the heuristic algorithm computes thousands of possible ways to fit the data with the model a unique solution is found, a causal inference is plausible.

Further, Cook (1993) regarded meta-analysis as a tool for seeking causal generalizations. According to Cronbach (1982), the two major themes of causal generalization in experimental research involve using sample data to make generalizations to the target population and across different populations. Cook claimed that meta-analysis probes both of Cronbach's types of causal generalizations because it synthesizes effect sizes across different studies using different samples and populations. Nonetheless, it is important to note that not all quantitative researchers who employ meta-analysis interpret the results in terms of causation.

Hoyle (1995) asserted that at least three criteria need to be fulfilled to validate a causal inference:

1. Directionality: The independent variable affects the dependent variable.

2. Isolation: Extraneous noise and measurement errors must be isolated from the study so that the observed relationship cannot be explained by something other than the proposed theory.

3. Association: The independent variable and the dependent variable are mathematically correlated.

To establish the direction of variables, the researcher can apply logic (e.g., physical height cannot cause test performance), theory (e.g. collaboration affects group performance), and most powerfully, research design (e.g., other competing explanations are ruled out from the experiment). To meet the criterion of isolation, careful measurement should be implemented to establish validity and reliability and to reduce measurement errors. In addition, extraneous variance, also known as threats against experimental validity, must be controlled for in the design of the experiment. Lastly, statistical methods are used to calculate the mathematical association among variables. However, in spite of a strong mathematical association, the causal inference may not make sense at all if directionality and isolation are not established. In short, all three components of quantitative research, i.e., experimental design, measurement, and statistical analysis, work together to establish the validity of cause and effect inferences. In brief, the anti-cause notion of logical positivism is incompatible with many branches of quantitative methods such as randomized experiments, quasi-experiments, latent construct theory, structural equation modeling, and, arguably, meta-analysis.

Downplaying explanation

It is not surprising that explanation, along with causality, is misidentified as a link between logical positivism and quantitative research. For instance, Langenbach et al. (1994) asserted that quantitative research, which is based on a positivist philosophy, seeks to explain the cause of changes in social facts.

On the contrary, positivists such as Schlick maintain that inquiry of knowledge describes what happens, but does not explain or prescribe it. While the spirit of quantitative research is to seek explanation, it demonstrates complex relationships among variables/constructs, rather than merely describing what happens. According to Bredo and Feinberg (1982), researchers who hold a realist position do not accept the positivist account of explanation as adequate. To the realist, an adequate explanation is one that can explain the phenomenon in terms of causal necessity, not just lawful regularity.

The covering law model, introduced by Hempel (1965), illustrates how positivists seek explanation in terms of regularity. In Hempel's view, to explain an event (S), a law (L) is applied and some particular facts (F) are observed to link S and L. This deductive approach is descriptive in nature and thus does not generate any new knowledge. For example,

L: Human behaviors are rational.

F: One of several options is more efficient in achieving the goal.

S: A rational human takes the option, which directs him to achieve his goal. (Anderson, 1990)

In this case, "rationality" is the term to describe the phenomenon that humans choose more efficient options. Interestingly enough, the descriptive approach of positivism is more compatible with phenomenological-oriented qualitative research than quantitative research. Quantitative researchers have a different view of explanation. In quantitative research, explanation implies a theoretical formulation about the nature of the relationship among the variables (Pedhazur, 1982). Within some theoretical frameworks it may be meaningful to compute semipartial correlations, whereas in others such statistics are not meaningful. In other words, the explanation in quantitative research is not entirely descriptive.

Explanation is tied to statistical modeling in SEM. According to Kelley (1998), very often there is a gap between the explanandum (that which is to be explained) and the explanation (hypothesis); a good explanation is capable of bridging the gap. Kelley pointed out that a gap exists in such a simple explanation as "a person is sad (explanandum) because her cat is dead (explanation)." Between the preceding explanandum and the explanation, one must prove that the person is emotionally attached to the cat. In research this gap is even wider, and that is why statistical modeling is necessary. For example, let's evaluate this statement: Children from Protestant families have better performance in school because of Protestant work ethics. To validate this explanation, many other statements/variables are needed to fill the gap:

X1: Protestant work ethics motivate people to work hard.

X2: Working hard accumulates more money.

X3: Parents who have more money will buy resources such as books and computers for their child's education.

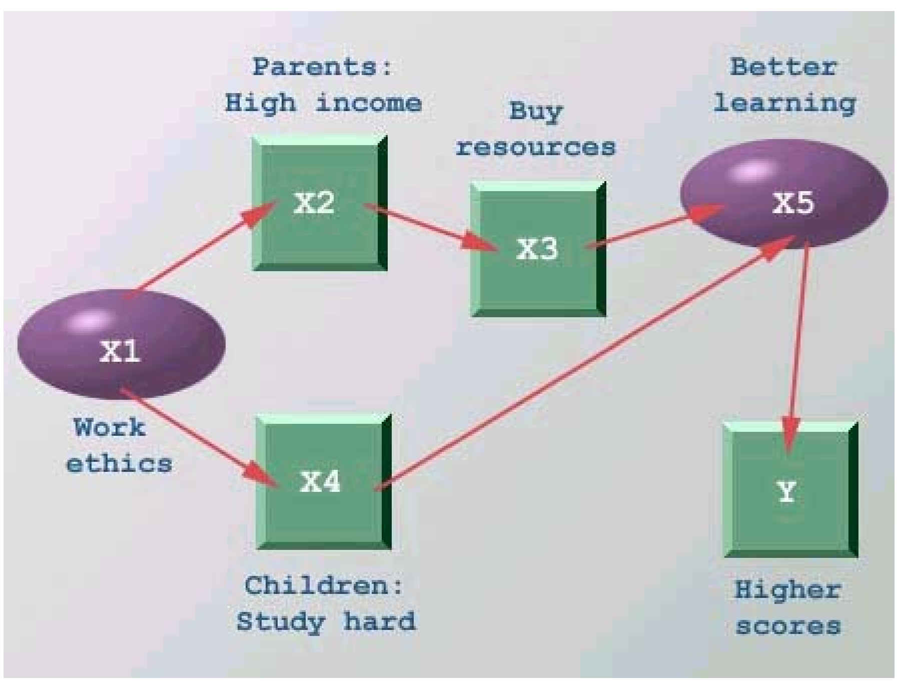
X4: Children who grow up in a Protestant family study harder.

X5: Hard-working children who are exposed to rich educational resources learn better.

Y: Children from Protestant families have better performance in school.

Assuming that we can re-express all of the above statements into measurable variables, a statistical model can be drawn as shown in Figure 1.

Figure 1. Relationships between the explanandum and explanation



In brief, statistical modeling plays the role of filling the gap between the explanandum and the explanation. Quantitative research definitely seeks explanation and thus does not subscribe to the positivist notion of downplaying explanation.

Anti-theoretical entities

As mentioned before, logical positivists restrict reality to the observable, reject causal inferences, and downplay explanation. Therefore, logical positivists are skeptical of unobservable and theoretical entities such as latent variables, or factors. Some qualitative researchers drew an association between quantitative research and logical positivism, which is synonymous with the scientific paradigm. Indeed, logical positivism is not the modern scientific paradigm because modern scientists have turned away from the logical positivist position of anti-theoretical entities. For example, in a discussion of the existence of a nucleus inside an electron, Schlick (1959) explicitly rejected unobservable theoretical entities. Obviously, this approach hinders scientists from exploring the subatomic world. No wonder Weinberg (1992) argued that the development of $20^{th}$ century physics was delayed by physicists who took positivism seriously and thus could not believe in atoms, let alone electrons or smaller particles. Meehl (1986) also pointed out that "it [logical positivism] is not an accurate picture of the structure of advanced sciences, such as physics; and it is grossly inadequate as a reconstruction of empirical history of science." (p. 315)

As a matter of fact, many quantitative researchers in the social sciences assert abstract theoretical constructs. Campbell (1995) maintained that factor analysis and multi-dimensional scaling must be theory-driven. In psychometrics, latent constructs such as self-esteem and intrinsic motivation are always hypothesized. Although Cronbach (1989) and Cronbach and Meehl (1955), who developed the concept of construct validity, had accepted the definitional operationalism, construct validity could be viewed as a product of a feedback loop between hypothetical, theoretical constructs and observable data. If the notion of anti-theoretical entities was imposed on quantitative research, a large portion of quantitative research regarding latent constructs would be impossible.

Anti-metaphysics

Logical positivists deny the existence of metaphysical and transcendental reality (Ayer, 1934; Carnap, 1959). Although both metaphysics and theoretical entities are unobservable, there is a difference between them. In the viewpoint of logical positivism, theoretical entities such as electronics belong to the physical world. As Schlick (1959) said, the world of science is the same as the world of our everyday life where memories, desires, ideas, stars, clouds, plants and animals exist. In philosophy, the metaphysical world is "the other world" beyond this physical realm. Logical positivism denies this metaphysical world.

On the other hand, many quantitative researchers do not necessarily reject the metaphysical existence. Mathematicians have developed a world of distributions and theorems. Essentially, statistical testing is a comparison between the observed statistic and theoretical distributions. Although statistical methods are considered empirical, Fisher (1956) asserted that theoretical sampling distributions could not be empirically reproduced. Actually, sampling distributions involve not only theoretical entities, but also mathematical reality, which has been a debatable topic in philosophy (Devitt, 1991; Drozdek & Keagy, 1994; Gonzalez, 1991; Penrose, 1989; Russell, 1919; Tieszen, 1992, 1995; Whitehead & Russell, 1950). On one hand, many mathematicians, statisticians, and quantitative researchers subscribe to the view that theoretical distributions are non-empirical but not metaphysical, and that they involve mathematical and logical truths. On the other hand, many view theoretical distributions and the broader mathematical realm as metaphysical.

Logical analysis and reductionism

Logical positivism adds an emphasis on logical analysis of language into positivism. According to Russell’s logical atomism (1959), complex phenomena could be expressed in terms of mathematics, and mathematics could be further reduced to logic. This idea was embraced by logical positivists such as Carnap (Coffa, 1991). Inspired by mathematical/logical reductionism, logical positivists went further to develop methods based upon analytic reductionism. In analytic reductionism, an observed relationship is broken down into the components that are necessary and sufficient for a relationship to occur (Cook, 1985). At first glance, this notion describes the practice of quantitative research, and thus certain researchers explicitly charged that quantitative research is mechanistic and reductionistic (e.g. Dootson, 1995). In quantitative research, the complexity of events is expressed in terms of manageable variables, numbers, and mathematical equations; statistical analysis is viewed as a process of data reduction. However, the link between reductionism and quantitative methods is questionable when one examines the issue carefully.

Although the previous section mentioned that quantitative researchers embrace theoretical constructs, quantitative research is by no means a one-way reduction from events to numeric data to mathematical models. Instead, events, data, and theory form a positive feedback loop. For example, when Cronbach and Meehl (1955) proposed the concept of construct validity, they maintained that hypothetical constructs drive the nature of data collection. In turn, the data resulting from the administration of the instrument are then used to revise the theory itself.

Unlike the positive loop in quantitative research, Russell's mathematical model is a formal analysis of a closed system. Russell is not concerned with what the reality is and whether geometric objects exist. The mission of mathematicians is to discover the logical relationships among objects. An axiom is considered valid just because Y logically entails X.

This line of thinking can be found among some quantitative researchers. For example, there is an old saying that "a statistical model is neither right nor wrong." This approach treats a mathematical model as a closed logical system; therefore empirical data does not constitute evidence to prove or disprove a model. Nonetheless, the belief that "all models are false" has become more popular (Bernardo & Smith, 1994; MacCallum, 1995). In this view, no data can fit any model perfectly, and thus all models are wrong to some degree. This saying indicated that quantitative research is an interaction between data and theory, rather than a one-way reduction from events to a logical-mathematical system.

Frequentist probability

Probability theory is considered a specific application of logical positivism to quantitative methods. Fisherian hypothesis testing is based upon relative frequency in the long run. Since a version of the frequentist view of probability was developed by positivists Reichenbach (1938) and von Mises (1964), the two schools of thought seem to share a common thread. However, this is not necessarily true. Both Fisherian and positivist frequency theory were proposed in opposition to the classical Laplacean theory of probability. In the Laplacean perspective, probability is deductive and theoretical. To be specific, this probability is deduced from theoretical principles and assumptions in the absence of verification by empirical data. Assuming that every member of a set has equal probability to occur (the principle of indifference), probability is treated as a ratio between the desired event and all possible events. This probability, derived from the fairness assumption, is made before any events occur.

Reichenbach and von Mises maintained that a very large number of empirical outcomes should be observed to form a reference class. Probability is the ratio of the frequency of desired outcome to the reference class. Indeed, the empirical probability hardly concurs with the theoretical probability in the classical sense. For example, when a die is thrown, in theory the probability of the occurrence of number "one" should be 1/6. But even in a million simulations, the actual probability of the occurrence of "one" is not exactly one out of six times. It appears that von Mises’s frequency theory is more valid than the classical one. However, the usefulness of this actual, finite, relative frequency theory is limited, for it is difficult to tell how large the reference class must be to be considered large enough.

Fisher (1930) argued that Laplace's theory is incompatible with the inductive nature of science. However, unlike the logical positivists' empirical-based theory, Fisher's is a hypothetical, infinite relative frequency theory. In the Fisherian school, various theoretical sampling distributions are constructed as references for comparing the observed. Fisher and Reichenbach developed their frequency theories independently. In the beginning of the 20th century, von Mises was not widely cited in statistics texts or debates of the Royal Statistical Society, in which Fisher was active (Howie, 2002). On the other hand, Salmon (1967), who is a student of Reichenbach, credited Reichenbach as the developer of the frequency theory without a single word about Fisher.

Although von Mises (1928/1957) mentioned Fisher’s work in his book entitled Probability, statistics, and truth, his discussion about the Fisherian notion of likelihood is negative:

> I do not understand the many beautiful words used by Fisher and his followers in support of the likelihood theory. The main argument, namely, that p is not a variable but an “unknown constant,” does not mean anything to me. It is interesting to note that some philosophers have already begun to expound “likelihood” as a new kind of probability which would not depend on relative frequencies. (p.158)

It is important to point out that probability, in Fisher’s sense, is hypothesis-oriented, while in the positivist’s view probability is empirically based. In Fisher’s view, likelihood is not the same as probability. Likelihood is the probability of the observed outcome (O) given the hypothesis (H) is true P(O|H). In contrast, positivists view probability as the possibility that the hypothesis is true given the observed data P(H|O). It is obvious that the frequentist positions taken by Fisher and von Mises are quite different.

Further, backed by thorough historical research, Hacking (1990) asserted that "to identify frequency theories with the rise of positivism (and thereby badmouth frequencies, since "positivism" has become distasteful) is to forget why frequentism arose when it did, namely when there are a lot of known frequencies" (p.452).

**Links between logical positivism and quantitative methods**

To be fair, there are several links between quantitative research and logical positivism in history. For instance, Stevens, the originator of the representation theory of measurement, adopted the ideas of logical positivism and operationalism (Michell, 1997). Cronbach and Meehl (1955), who developed construct validity, also accepted operationalism within the positivist framework. One of the most obvious links between positivism and quantitative methods could be found in Karl Pearson. Pearson, the inventor of the correlation coefficient, was a follower of Comte's positivism (Peirce, 1954). According to Pearl (2000), Pearson denied any need for an independent concept of causation beyond correlation. Nevertheless, although Pearson downplayed causal explanation, his view should not be equated with the logical positivists’ anti-cause notion. Pearson admitted that correlation analysis might be misleading because of spurious correlation. In other words, behind the two highly correlated variables, there might be other variables acting as common causes. The ultimate objective of research was to find evidence of an "organic relationship," which was "causal or semi-causal" (Aldrich, 1995). Harold Jeffreys, who endorsed Bayesian methods in probabilistic inferences, was influenced by Pearson's epistemology. However, later Jeffreys became skeptical to Pearson's anti-cause view. Jeffreys believed that the data he collected in astronomy could be used to infer causes (Howie, 2002).

Further, the development of Cronbach's construct validity has been moving away from operationalism to multi-operationism (Cook, 1985). The modern concept of construct validity is in sharp contrast to the classical sense of operationalism. In classical operationalism, every term is narrowly defined by a specific set of operations, which become its sole empirical referent. In modern construct validity, a measure is taken to be one of an extensive set of indicators of the theoretical construct. In this spirit, multiple items are loaded into a latent factor using factor analysis. Because the sets of indicators are extensible and often probabilistically related to the theoretical construct as well as to each other, constructs are not "operationally" defined, but are more like "open concepts" (Salvucci, Walter, Conley, Fink, & Saba, 1997). More importantly, as mentioned before, in causal inferences Cronbach did not adopt the narrow view of positivist epistemology, in which only verifiable statements are considered meaningful. Constructs could be generated through qualitative methods (Cook, 1991).

## Implications for triangulation

### Beyond positivism

The above discussion is devoted to stressing the view of continuity in research traditions rather than the notion of incommensurability in paradigms, and also to unlinking logical positivism and current quantitative methodology. Both of these ideas have important implications for researchers. When quantitative research does not aim at using fixed categories and discovering one objective reality, it opens the door to a richer interpretation of research findings even though there is more than one answer. To be specific, statisticians would not be embarrassed by different probabilities yielded from Bayesian inferences and the frequentist approach; by the same token, measurement experts could allow psychometric attributes returned from classical item analysis, Rasch models, two-parameter models, and three-parameter models to coexist. Also, open concepts and modified instruments are encouraged in varying contexts.

At first glance, this seems to be a dangerous notion of relativism that could hinder research endeavors from reaching a conclusive closure. But it is not. Different methods are tied to different contexts such as the properties of the sample/population and the assumptions imposed on the research methods. Woodward (1998, 1999, 2000, 2001) and Hausman and Woodward (1999) asserted that statistical findings are not universal. Rather, they could be just invariant and robust within a limited range of circumstances. Moreover, the nature of probabilistic and statistical approaches could be interpreted in Bohr’s conception of experimentation. One can answer questions of the form: "If the experiment is performed, what are the possible results and their probabilities?" One should not answer any question in this form: "What is really happening when ...?" (cited in Jaynes, 1995, p.1012). If seeking a single answer is not the goal of quantitative research, mixing various qualitative and quantitative methods for triangulation could be promising.

<u>Post-positivism, critical realism, and critical multiplism</u>

If logical positivism is not the underlying philosophy of quantitative methodology, then what philosophy can it fit into? As mentioned in the beginning, several philosophical foundations such as critical realism, critical multiplism, and post-positivism have currently been proposed. Post-positivism and critical realism are classified under the same umbrella by Letourneau and Allen (1999). However, this classification may be questionable. Post-positivism is a philosophy that views theories as socially constructed linguistic systems, which are ultimately underdetermined; and truths are also ultimately unknowable. Following the direction of post-positivism, research endeavors should be devoted to translation and comparison of various “languages” in the hope of reaching warranted assertions (Laudan, 1996). Out of frustration with this under-determination thesis, Laudan (1996) used the phrase “the sins of the fathers” (p.3) to criticize that post-positivism inherits this problematic feature from logical positivism. Critical realism, on the other hand, accepts the existence of an objective reality, but asserts that claims about reality must go through critical examinations (Guba & Lincoln, 2000). Nonetheless, through critical examinations knowledge about this objective world is possible (Patomaki & Wight, 2000). Although critical realism is said to be epistemological relative, its ontology is by no means relative. In other words, in critical realism the first part (critical) is about epistemology and methodology while the second part (realism) is concerned with ontology. Obviously, tensions exist between post-positivism and critical realism. Post-positivism tends to pull researchers away from asserting an objective reality while critical realism tends to push researchers towards the assertion of a real world. Nevertheless, critical multiplism does not necessarily view the world as a linguistic description or a reality that is independent of our language.

Furthermore, like logical positivism, several post-positivists maintain that metaphysics is still outside the boundary of science (Bronowski, 1965/1972). On the contrary, critical realists perceive that the reality consists of unobservable elements beyond our empirical realm, but they are still reachable by scientific inquiry (Clark, 1998). In the section regarding major theses of logical positivism, it has been pointed out that some quantitative researchers do accept metaphysical notions such as infinite distributions and mathematical axioms. In this sense, post-positivism and quantitative methodology may not be fully compatible.

Certain critical realists assert that while experimentation is possible in natural sciences, it is impossible in social sciences because in the former manipulation is conducted in a closed system, but in the latter social activities occur only in an open system. Further, social sciences deal with meanings and concepts that can only be understood, but not measured (Warner, 2001). This notion may alienate critical realism from the majority of quantitative researchers. It is a well-known fact that many quantitative researchers do believe that experimentation could be implemented in social sciences and concepts could be measured by numeric means. Taking all of the above into consideration, it may be better not to put post-positivism and critical realism together as the supporting philosophies for quantitative methodology.

Various schools in quantitative research, such as Bayesianism, Fisherianism, Exploratory Data Analysis, Confirmatory Data Analysis, and so on, carry different philosophical assumptions, and could be treated as independent research traditions. Nevertheless, given the richness and diversity of various quantitative methodologies, it is the author's belief that critical multiplism could be a meta-research-tradition for unifying quantitative methodologies. More importantly, critical multiplism, a philosophy that encourages using multiple sources of data and research techniques, provides a logical path to triangulation.

Triangulation

There are two major goals of triangulation, namely, convergence and completeness. The notion of scientific convergence could be traced back to American philosopher Charles Sanders Peirce. According to Peirce (1934/1960), academic inquiry is a self-correcting and "limiting" process contributed by the research community. The notion of "limiting" may be counterintuitive. In this context "limiting" does not mean the limitations or drawbacks of research methodologies. Rather, it should be comprehended as a mathematical concept. For example, according to the Central Limit Theorem, the variance of sample statistics would be reduced as more samples are drawn. This notion, in Peirce's view, could be well-applied to research endeavors. In spite of short-run variances and discrepancies, long-run convergence might be resulted from the multitude and variety of different inquiries. This form of convergence acts as a "cable" for linking various arguments and evidence.

In recent years, mixing methods has been proposed by certain researchers (e.g. Johnson & Onwuegbuzie, 2004; Webb et al, 1981;) in attempt to reach convergent validity or a more warranted assertion. On the other hand, other researchers (e.g. Jick, 1983) countered that different results yielded from various methods should not be used to validate each other; rather, these differences should be retained so that a more complete picture of the phenomenon under investigation could be seen. For example, Fielding & Fielding (1996) asserted that "We should combine theories and methods carefully and purposefully with the intention of adding breadth and depth to our analysis, but not for the purpose of pursuing objective truth." (p.33)

Actually, convergence and completeness might not be contradictory. It is important to point out that seeking convergence is not the same as looking for one single answer representing an objective truth. Clearly, this notion has been rejected in the previous discussion. Rather, convergence shows a **pattern** of different research results while retaining the residuals departing from the pattern. Take regression as an example. It is extremely rare to obtain a straight line going through all data points in a scattergram. Instead, data points scatter around the plot and each point carries a different degree of residuals. The regression line summarizes the pattern of the data; at the same time, the data points and the residuals depict the complexity and the fitness of the model. By the same token, different results obtained by different methods based upon different research traditions are like data points in a scatterplot, and the smoothed regression line is like the converged pattern in a mixed method study. Using the cable metaphor introduced by Peirce again, a regression line is a “cable” linking all points within a single data set within the same research approach, while triangulation is a “cable” tying together all results from different research traditions. Completeness and convergence, indeed, could go hand in hand.

## Conclusion

In the early 20th century, logical positivism was popular in both natural and social sciences, and thus experimental methods were developed under the influence of logical positivism. However, cultures, including the academic culture, receive influences from multiple sources. For example, several impressionists drew ideas from photography and Japanese printing, yet an art history professor would not stretch to claim that impressionism is based upon Japanese art or photography. By the same token, the statement that quantitative research is based on logical positivism ignores the dynamic complexity of the academic culture, in which multiple research traditions could interact and compete with each other. Also, the academic culture is evolving. As mentioned in the beginning, many philosophers of science have rejected logical positivism. Relating an outdated philosophy to quantitative research may discourage social science researchers from using this research approach, and also lead to misguided dispute between quantitative and qualitative researchers (e.g., McLaughlin, 1991; Rennie, 1999). What is needed is to encourage researchers to keep an open mind to different methodologies by allowing research methods being driven by research questions (Leech & Onwuegbuzie, 2004; Onwuegbuzie & Leech, 2005), while retaining skepticism to examine their philosophical assumptions of various research methodologies instead of unquestioningly accepting popular myths.

As mentioned in the beginning, newer epistemologies and methodologies that allow for rival theories and methods to be integrated, such as critical multiplism and triangulation, have emerged. In the spirit of critical multiplism and triangulation, researchers should be encouraged to employ mixed methods, including qualitative and quantitative approaches. Within the quantitative school, different approaches, such as hypothesis testing, meta-analysis, EDA, Bayesian inference, structural equation modeling, and many others, should be considered based upon the research question and the data structure.

**Acknowledgments**

I would like to express my gratefulness to Ms. Samantha Waselus and Mr. Shawn Stockford for their professional editing, and also Professor Samuel Green, and Professor Marilyn Thompson for their valuable input.

**References**

Abbot, A. (1998). Causal devolution. Sociological Methods and Research, 27, 148-179.

Aldrich, J. (1995). Correlations genuine and spurious in Pearson and Yule. Statistical Science, 10, 364-376.

Anderson, J. R. (1990). The adaptive character of thought. Hillsdale, NJ: Erlbaum.

Ayer, A. J. (1934). Demonstration of the impossibility of metaphysics. Mind (New Series), 43, 335-345.

Ayer, A. J. (1936). The principle of verifiability. Mind (New Series), 45, 199-203.

Ayer, A. J. (1946). Language, truth, and logic (2nd ed). London: V. Gollancz.

Behrens, J. T. (1997). Principles and procedures of exploratory data analysis. Psychological Methods, 2, 131-160.

Behrens, J. T., & Yu, C. H. (2003). Exploratory data analysis. In J. A. Schinka & W. F. Velicer, (Eds.), Handbook of psychology Volume 2: Research methods in Psychology (pp. 33-64). New Jersey: John Wiley & Sons, Inc.

Berg, B. L. (2001). Qualitative research methods for the social sciences. Boston, MA: Allyn & Bacon.

Berger, J. (2000). Bayesian analysis: A look at today and thoughts of tomorrow. Journal of American Statistical Association, 95, 1269-1276.

Berger, J. (2001, August). Could Fisher, Jeffreys, and Neyman have agreed on testing? Paper presented at the Joint Statistical Meeting , Atlanta, GA.

Bernardo, J. M., & Smith, A. F. M. (1994). Bayesian theory. Chichester, NY: John Wiley & Sons.

Blalock, H. M. (1964). Causal inferences in nonexperimental research. Chapel Hill: University of North Carolina Press.

Bogdan, R., & Taylor, S. (1975). Introduction to qualitative research: A phenomenological approach to the social sciences. New York: John Wiley & Sons.

Borsboom, D., Mellenbergh, G. J., & van Heerden, J. (under review). Philosophy of science and psychometrics: Reflections on the theoretical status of the latent variable.

Bredo, E., & Feinberg, W. (1982). The positivist approach to social and educational research. In E. Bredo & W. Feinberg (Eds.), Knowledge and values in social and educational research (pp. 13-27). Philadelphia: Temple University Press.

Bronowski, J. (1965/1972). Science and human values. New York: Harper and Row.

Campbell, D. T. (1995). The postpositivist, nonfoundational, hermeneutic epistemology exemplified in the works of Donald W. Fiske. In P. E. Schrout & S. T. Fiske (Eds.), Personality research, methods, and theory: A festschrift honoring Donald W. Fiske (pp. 13-27). Hillsdale, NJ: Lawrence Erlbaum Associates.

Carnap, R. (1937). The logical syntax of language. London: Routledge & Kegan Paul Ltd.

Carnap, R. (1959). The elimination of metaphysics through logical analysis of language. In A. J. Ayer (Ed.), Logical positivism (pp. 60-81). New York: Free Press.

Christensen, L. B. (1988). Experimental methodology. Boston: Allyn and Bacon.

Clark, A. M. (1998). The qualitative-quantitative debate: Moving from positivism and confrontation to post-positivism and reconciliation. Journal of Advanced Nursing, 27, 1242-1249.

Coffa, J. A. (1991). The semantic tradition from Kant to Carnap. New York: Cambridge University Press.

Cook, T. D. (1985). Post-positivist critical multiplism. In R. L. Shotland & M. M. Mark (Eds.), Social science and social policy (pp. 21-62). Beverly Hills, CA: Sage.

Cook, T. D. (1991). Clarifying the warrant for generalized causal inferences in quasi-experimentation. In M. W. McLaughlin & D. Phillips (Eds.), Evaluation and education at quarter century (pp. 115-144). Chicago: NSSE.

Cook, T. D. (1993). A quasi-sampling theory of the generalization of causal relationships. In L. Sechrest & A. G. Scott (Eds.), Understanding causes and generalizing about them (pp. 39-83). San Francisco, CA: Jossey-Bass.

Cook, T. D., & Campbell, D. T. (1979). Quasi-experimentation: Design and analysis issues for field settings. Boston, MA: Houghton Mifflin Company.

Cook, T. D., & Shadish, W. R. (1994). Social experiments: Some developments over the past fifteen years. Annual Review of Psychology, 45, 545-580.

Cronbach, L. J. (1982). Designing evaluations of educational and social programs. San Francisco, CA: Jossey-Bass.

Cronbach, L. J. (1989). Construct validation after thirty years. In R. L. Linn (Ed.), Intelligence: Measurement, theory, and public policy (pp. 141-171). Urbana, IL: University of Illinois Press.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. Psychological Bulletin, 52, 281-302.

Devitt, M. (1991). Realism and truth (2nd ed.). Cambridge, MA: B. Blackwell.

Dootson, S. (1995). An in-depth study of triangulation. Journal of Advanced Nursing, 22, 183-187.

Drozdek, A., & Keagy, T. (1994). A case for realism in mathematics. Monist, 77, 329-344.

Embretson, S., & Reise, S. P. (2000). Item response theory for psychologists. New Jersey: LEA.

Erlandson, D. A., Harris, E. L., Skipper, B. L., & Allen, S. D. (1993). Doing naturalistic inquiry: A guide to methods. Newbury Park, CA: Sage Publications.

Feldman, M. (1998, February 28). Re: Rethinking quantitative social research. Statistical consulting newsgroup. [Online]. Available Newsgroup: sci.stat.consult [1998, February 28].

Fielding, N., & Fielding, J. (1986). Linking data. Beverly Hills, CA: Sage Publications.

Fisher, R. A. (1930). Inverse probability. Proceedings of the Cambridge Philosophical Society, 26, 528-535.

Fisher, R. A. (1956). Statistical methods and scientific inference. Edinburgh: Oliver and Boyd.

Friedman, M. (1991). The re-evaluation of logical positivism. The Journal of Philosophy, 88, 505-519.

Glaser, B. G., & Strauss, A. L. (1967). Discovery of grounded theory: Strategies for qualitative research. Chicago, IL: Aldine Pub. Co.

Glesne, C., & Peshkin, A. (1992). Becoming qualitative researchers: An introduction. New York : Longman.

Gliner, J. A., & Morgan, G. A. (2000). Research methods in applied settings: An integrated approach to design and analysis. Mahwah, N.J.: Lawrence Erlbaum Associates.

Glymour, C. (1982). Causal inference and causal explanation. In R. McLaughlin (Ed.), What? Where? When? Why? Essays on induction, space, and time, explanation (pp. 179-191). Boston, MA: D. Reidel Publishing Company.

Glymour, C. (1986). Comments: Statistics and metaphysics. Journal of the American Statistical Association, 81, 964-966.

Glymour, C., Scheines, R., Spirtes, P., & Kelly, K. (1987). Discovering causal structure: Artificial intelligence, philosophy of science, and statistical modeling. Orlando, FL: Academic Press, Inc.

Gonzalez, W. J. (1991). Intuitionistic mathematics and Wittgenstein. History and Philosophy of Logic, 12, 167-183.

Guba, G., & Lincoln, E. (1994). Competing paradigms in qualitative research. In N. K. Denzin, & Y. S. Lincoln (Eds.), Handbook of qualitative research (pp. 105-117). Thousand Oaks, CA: Sage Publications.

Hacking, I. (1983). Representing and intervening: Introductory topics in the philosophy of natural science. New York: Cambridge University Press.

Hacking, I. (1990). In praise of the diversity of probabilities. Statistical Science, 5, 450-454.

Hausman, D., & Woodward, J. (1999). Independence, invariance, and the Causal Markov Condition. British Journal of Philosophy of Science, 50, 521-583.

Hempel, C. G. (1965) Aspects of scientific explanation and other essays in the philosophy of science. New York: Free Press.

Howe, K.R (1988). Against the quantitative-qualitative incompatibility thesis (or dogmas die hard). Educational Researcher, 17, 10-16.

Howie, D. (2002). Interpreting probability: Controversies and developments in the early twentieth century. Cambridge, UK: Cambridge University Press.

Howson, C., & Urbach, P. (1993). Scientific reasoning: The Bayesian approach. Chicago, IL: Open Court.

Hoyle, R. H. (Ed.) (1995). Structural equation modeling: Concepts, issues, and applications. Thousand Oaks, CA: Sage Publications.

Huysamen, G. K. (1997). Parallels between qualitative research and sequentially performed quantitative research. South African Journal of Psychology, 27, 1-9.

Jaynes, E. T. (1995). Probability theory: The logic of science. [On-line] Available URL: http://omega.math.albany.edu:8008/JaynesBook.html

Jick, T. (1983). Mixing qualitative and quantitative methods: Triangulation in action. In Van Mannen (Ed.), Qualitative methodology (pp. 135-148). Beverly Hills, CA: Sage Publications.

Johnson, B., & Onwuegbuzie, A. J. (2004). Mixed methods research: A research paradigm whose time has come. Educational Researcher, 33, 14-26.

Kelley, D. (1998). The art of reasoning (3rd ed.). New York: W. W. Norton & Co.

Kline, R.B. (1998). Principles and practice of structured equation modeling. New York: The Guilford Press.

Kuhn, T. (1962). The structure of scientific revolutions. Chicago: University of Chicago Press.

Langenbach, M., Vaughn, C., & Aagaard, L. (1994). An introduction to educational research. Boston, MA: Allyn and Bacon.

Laudan, L. (1977). Progress and its problems: Toward a theory of scientific growth. Berkeley, CA : University of California Press.

Laudan, L. (1996). Beyond positivism and relativism: Theory, method, and evidence. Boulder, CO: Westview Press.

Leech, N. L., & Onwuegbuzie, A. J. (2004 April). A typology of mixed research designs. Paper presented at the Annual Meeting of the American Educational Research Association, Montreal, Canada.

Lehmann, E. L. (1993). The Fisher, Neyman-Pearson theories of testing hypotheses: One theory or two? Journal of the American Statistical Association, 88, 1242-1249.

Letourneau, N., Allen, M. (1999). Post-positivistic critical multiplism: A beginning dialogue. Journal of Advanced Nursing, 30, 623-630.

Luker, B., Luker, B., Jr., Cobb, S. L., & Brown, R. (1998). Postmodernism, institutionalism, and statistics: Considerations for an institutionalist statistical method. Journal of Economic Issues, 32, 449-457.

MacCallum, R. C. (1995). Model specification: Procedures, strategies, and related issues. In R. H. Hoyle (Ed.), Structural equation modeling: Concepts, issues, and applications (pp.16-36). Thousand Oaks, CA: Sage Publications.

McLaughlin, E. (1991). Oppositional poverty: The quantitative/qualitative divide and other dichotomies. Sociological Review, 39, 292-308.

Meehl, P. E. (1986). What social scientists don't understand. In D. W. Fiske & R. A. Schweder (Eds.), Metatheory in social science. Chicago: University of Chicago Press.

Merriam, S. B. (1998). Qualitative research and case study: Applications in education. San Francisco, CA: Jossey-Bass.

Michell, J. (1997). Quantitative science and the definition of measurement in psychology. British Journal of Psychology, 88, 355-386.

Miles, M., & Huberman, A. (1984). Qualitative data analysis. Beverly Hills, CA: Sage Publications.

Nation, J. R. (1997). Research methods. Upper Saddle River, NJ: Prentice Hall.

Onwuegbuzie, A. J., & Leech, N. L. (2005b, February). Linking research questions to mixed methods data analysis procedures. Paper presented at the annual meeting of the Southwest Educational Research Association, New Orleans, LA.

Patomaki, H., & Wight, C. (2000). After postpositivism? The promises of critical realism. International Studies Quarterly, 44, 213-239.

Pawitan, Y. (2000). Likelihood: Consensus and controversies. Paper presented at the Conference of Applied Statistics in Ireland.

Pawitan, Y. (2001). In all likelihood: Statistical modeling and inference using likelihood. New York: Oxford University Press.

Pearl, J. (2000). Causality: Models, reasoning, and inference. Cambridge, UK: Cambridge University Press.

Pedhazur, E. J. (1982). Multiple regression in behavioral research: Explanation and predication (2nd ed.). Forth Worth, TX: Harcourt Brace College Publishers.

Peirce, C. S. (1934/1960). Collected papers of Charles Sanders Peirce. Cambridge: Harvard University Press.

Peirce, C. S. (1954). Notes on positivism. In P. P. Wiener (Ed.), Charles S. Peirce selected writing: Values in a universe of chance (pp.137-141). New York: Dover Publications.

Penrose, R. (1989). The emperor's new mind: Concerning computers, minds, and the laws of physics. Oxford: Oxford University Press.

Phillips D. (1987). Philosophy, science and social Inquiry. New York: Pergamon Press.

Phillips D. (1990a). Postpositivistic science: Myths and realities. In E. G. Guba (Ed.), The paradigm dialogue (pp. 31-45). Newbury Park, CA: Sage.

Phillips D. (1990b). Subjectivity and objectivity: An objective inquiry. In E. W. Eisner & A. Peshkin (Eds.), Qualitative inquiry in education: The continuing debate (pp.19-37). New York: Teachers College Press.

Phillips D. C. (1992). The social scientist's bestiary: A guide to fabled threats to, and defences of, naturalistic social science. New York: Pergamon Press.

Phillips, D. C. (2000). The expanded social scientist's bestiary. New York: Rowman & Littlefield.

Phillips, D. C., & Burbules, N. (2000). Postpositivism and educational research. New York: Rowan & Littlefield.

Phillips, J. (1988). Diggers of deeper holes. Nursing Science Quarterly, 1, 149-151.

Popper, K. R. (1959). Logic of scientific discovery. London: Hutchinson.

Popper, K. R. (1974). Replies to my critics. In P. A. Schilpp (Ed.), The philosophy of Karl Popper (pp.963-1197). La Salle, IL.: Open Court.

Reichardt, C. S., & Cook, T. D. (1979). Beyond qualitative versus quantitative methods. In T. D. Cook & C. S. Reichardt (Eds.), Qualitative and quantitative methods in evaluation research (pp. 7-32). Beverly Hills, CA: Sage Publications.

Reichenbach, H. (1938). Experience and prediction: An analysis of the foundations and the structure of knowledge. Chicago, IL: University of Chicago Press.

Rennie, D. L. (1999). A matter of hermeneutics and the sociology of knowledge. In M. Kopala & L. A. Suzuki (Eds.), Using qualitative methods in psychology (pp. 3-14). Thousand Oaks, CA: Sage Publications.

Russell, B. (1913). On the notion of cause. Proceeding of Aristotelian Society (New Series), 56, 26-27.

Russell, B. (1919). Introduction to mathematical philosophy. London: Allen & Unwin.

Russell, B. (1959). Logical atomism. In A. J. Ayer (Ed.), Logical positivism (pp. 31-52). New York: Free Press.

Salmon, W. C. (1967). The foundations of scientific inference. Pittsburgh: University of Pittsburgh Press.

Salvucci, S., Walter, E., Conley, V, Fink, S, & Saba, M. (1997). Measurement error studies at the National Center for Education Statistics. Washington D. C.: U. S. Department of Education.

Sanders, J. T. (1993). Dimensions of scientific thought. Nashville, TN: Camnichael & Carmichael, Inc..

Schlick, M. (1959). Positivism and realism. In A. J. Ayer (Ed.), Logical positivism (pp. 82-107). New York: Free Press.

Schlick, M. (1925/1974). General theory of knowledge. New York: Springer-Verlag.

Schuldenfrei, R. (1972). Quine in perspective. Journal of Philosophy, 69, 5-16.

Tieszen, R. (1992). Kurt Godel and phenomenology. Philosophy of Science, 59, 176-194.

Tieszen, R. (1995). Mathematical realism and Godel's incompleteness theorem. In P. Cortois (Ed.), The many problems of realism (pp.217-246). Tilburg, Netherlands: Tiburg University Press.

Tukey, J. W. (1977). Exploratory data analysis. Reading, MA: Addison-Wesley Publishing Company.

Tukey, J. W. (1980). We need both exploratory and confirmatory. The American Statistician, 34, 23-25.

Vincent, D. F. (1953). The origin and development of factor analysis. Applied Statistics, 2, 107-117.

von Mises, R. (1928/1957). Probability, statistics, and truth. London: The Macmillan Company.

von Mises, R. (1964). Mathematical theory of probability and statistics. New York: Academic Press.

Warner, M. (2001). Objectivity and emancipation in learning disabilities: Holism from the perspective of critical realism. Journal of learning disabilities, 26, 311-325.

Watkins, J.(1985). Science and skepticism. Princeton, NJ: Princeton University Press.

Webb, E. J., Campbell, D. T., Schwartz, R. D., Schrest, L., & Grove, J. B. (1981). Nonreactive measures in the social sciences. Boston, MA: Houghton Mifflin.

Weinberg, S. (1992). Dreams of a final theory. New York: Pantheon Books.

Werkmeister, W. H. (1937a). Seven theses of logical positivism critically examined I. The Philosophical Review, 46, 276-297.

Werkmeister, W. H. (1937b). Seven theses of logical positivism critically examined II. The Philosophical Review, 46, 357-376.

Whitehead, A. N., & Russell, B. (1950). Principia mathematica (2nd ed.). Cambridge, UK: Cambridge University Press.

Woodward, J. (1998). Causal independence and faithfulness. Multivariate Behavioral Research, 33, 129-148.

Woodward, J. (1999). Causal interpretation in systems of equations. Synthese, 121, 199-247.

Woodward, J. (2000). Explanation and invariance in the special sciences. British Journal of Philosophy of Science, 51, 197-254.

Woodward, J. (2001). Causation and manipulability. Stanford Encyclopedia of Philosophy. [On-line] Available: http://plato.stanford.edu/entries/causation-mani/

Yu, C. H. (2001). Philosophical foundations of causality in statistical modeling. Research Method Forum, 6. [On-line] Available URL: http://www.aom.pace.edu/rmd/2001forum.html