A Miracle of Measurement or Accidental Constructivism?

How PLS Subverts the Realist Search for Truth

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Design/methodology/approach

We present the philosophical foundations of scientific realism and constructivism, and examine the extent to which PLS aligns with them.

Purpose

To determine whether PLS is fit for purpose for scholars holding scientific realist views.

Findings

PLS does not align with scientific realism but aligns well with constructivism.

Research limitations/implications

Research is needed to assess PLS's fit with instrumentalism and pragmatism.

Practical Implications

PLS has no utility as a realist scientific tool, but may be of interest to constructivists.

Originality

The study is the first to assess PLS's alignments and mismatches with constructivist and scientific realist perspectives.

Keywords: Composites; PLS Partial Least Squares; Structural Equation Models; Antirealism, Instrumentalism, and Pragmatism; Unobservable Conceptual Variables; Latent Variables; Theory; Scientific Realism; Constructivism; Causality; Truth and Facts.

This paper examines PLS for its alignments with two ontological stances: scientific realism[1] and constructivism[2]. Realism and constructivism are at odds with each other, built on fundamentally diverging beliefs about the nature of knowledge, and how it is generated and justified. This conflict is seen clearly when one looks at the 'science wars', which began in the early 1980s, and are the disagreements between constructivists, who argue that it makes little sense to claim that there is objective truth, since all facts are constructed by humans, not discovered (Collin, 2017), and scientific realists, the self-styled "defenders of the 'objective truth' derived from scientific investigation … [and] of rationality and realism" (Linker, 2001, p. 59).

In marketing, apart from several early skirmishes (see Hunt, 1990; 1991; 1992; Peter, 1992; Zinkhan and Hirschheim, 1992), the science wars remain low key. Yet, an inadvertent science war of kinds is taking place, deep within scientific marketing territory. How? Unbeknown to many in the marketing field, to the realists who are seeking to identify marketing truths, one of the core tools that they may use, partial least squares path modeling (PLS)[3], is subverting their search for truth. Rather like a Trojan Horse, PLS *appears*

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[1] Being a scientist does not require one to view the world through the lens of realism. As Gergen and Gergen (2007, p. 463) note, some who do science may see the role of science as being the generation of "pragmatic or instrumental truths" (pragmatism is not necessarily a realist view, and instrumentalism definitely is not: we briefly discuss the use of PLS for instrumental or pragmatic purposes later in this paper).

[2] The general terms constructivist and constructivism are used throughout the paper to cover the many sorts of constructivism that are relevant to the current work, including certain kinds of social constructivism, critical theory, radical postmodernism, extreme relativism, strong constructivism, and various other kinds of antirealism (for more discussion, see: Chakravartty, 2007; Eberle, 2019; Kukla, 2000; Weinberg, 2014).

[3] In this paper, the term 'PLS' denotes partial least squares path modelling, and is used synonymously with related terms, such as PLS approach, PLS technique, PLS package, PLS modelling, PLS method, and PLS tool. Furthermore, the term PLS presently refers to the kind of PLS that Hair *et al.* (2019) and Dijkstra and Henseler (2015) promote. Numerous other terms describe this sort of PLS, such as PLS, PLS-SEM, PLS-PM, ordPLS, robust PLS, PLSc, ordPLSc, robust PLSc, and MCMQ. Although some of these terms denote slight differences in the analytic model/process used, such differences do not affect the paper's core arguments, which apply equivalently across them all. The term PLS, therefore, is used as a catch-all. However, PLS belongs to a broad family of Confirmatory Composite Analysis (CCA) estimators (see Schuberth, 2020), methods that are based on designing composite variables. While it is possible that the logics presented here extend to these latter approaches, the current paper does not formally address such matters. Finally, the discussions of PLS are not targeted at PLSe1 or PLSe2: "labeling these [latter] techniques as 'PLS' is misleading because parameters are

appropriate for testing scientific theories, with some claiming it to be "an important statistical technique in the toolbox of methods that researchers in marketing" should adopt (Hair *et al.*, 2019, p. 566). Articles in applied business research journals present PLS as a method akin to a magic bullet (Hair *et al.*, 2011)—a panacea for all kinds of practical research challenges for scientists (Hair *et al.*, 2019). Yet at the same time, the claims that PLS advocates make are heavily criticized within the methodological community, with scholars calling for its use to be rethought, and even that it be abandoned (e.g., Antonakis *et al.*, 2010; McIntosh *et al.*, 2014; Rönkkö and Evermann, 2013; Rönkkö *et al.*, 2016).

This paper adopts an alternative approach to the discussion of PLS, introducing issues not covered by the mainly numerical and technical critiques referred to above. Specifically, the paper seeks to assess the extent to which PLS is consistent with scientific realism's core assumptions, and/or is consistent with constructivism. In what follows, then, the key differences between the realist and constructivist approaches to knowledge and knowledge generation are outlined. Second, a spotlight is shone on the core methodology underpinning the PLS approach. Third, the analysis shows that the PLS methodology is almost entirely consistent with constructivism, in that the numerical results, predictions, and relationships that the PLS method returns are not estimates of real world things, but are explicitly constructed by the analysis method and (hence) the analyst. The paper concludes with a discussion of the implications, namely that PLS is unsuitable for those adopting scientific realism.

Constructivism

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estimated by fitting the model to a covariance matrix instead of calculating composite approximations" (see Rönkkö *et al.*, 2016, p. 21).

Constructivism holds that “many (or most, or all) phenomena that we normally assume are independently existing parts of the world around us are really just products of collective human action, thought, discourse, or other social practices” (Collin, 2017, p. 455), and that as a result, science and scientific knowledge are “a mere ‘social construction,’ a product of social forces through and through” (p. 457). As Latour and Woolgar (1986) put it, “scientific activity comprises the construction and sustenance of fictional accounts which are sometimes transformed into stabilised objects” (p. 235). For these authors, there is no one fixed reality, since “facts are constructed through operations… reality is the consequence rather than the cause of this construction, [and] a scientist's activity is directed, not toward ‘reality,’ but toward these operations” (p. 237). By “being sufficiently convincing”, a supposed scientific claim can “move toward a fact-like status. Instead of being a figment of one's imagination (subjective), it will become a ‘real objective thing,’ the existence of which is beyond doubt” (p. 241). As a result, “Scientific activity is not ‘about nature,’ it is a fierce fight to *construct* reality” (p. 244).

Thus, the proponents of constructivism argue that scientific facts are merely fabricated stories (Latour and Woolgar, 1986) and that it is false to claim that there is an “intrinsic nature of reality” (Rorty, 1998, p. 2). This philosophical feature of constructivism manifests itself through the doctrine of equal validity, which claims that “any culturally accepted theory of truth has a claim to validity equal to that of any other” (Merton, 1973b, p. 13). For constructivists, “there is no God’s eye point of view from which to adjudicate between [these many truths]” (Zackariasson, 2018, p. 3).

Thus, from such a perspective, facts are not *discovered* or found, since there does not exist an objective truth to be located and unearthed: knowledge is *built* (Lyotard, 1984). Different groups, peoples, societies, construct their own knowledge which may contradict the knowledge of others – and yet, importantly, for the constructivist, "the way the world is, independent of the knower, does not factor into [the nature of knowledge]" (Boghossian, 2012, p. 75), and so what is knowledge in one social setting may not be knowledge in another, and vice versa. For the constructivist, this state-of-affairs *is* the intrinsic nature of knowledge – "knowledge is derived …in the service of …vested interests" (Burr, 2015, p. 9). Proponents of the strongest forms of constructivism claim that "all facts are constructed […and so] there is no independent reality" (Kukla, 2000, p. 25) to know.

Scientific Realism

On the other hand, scientific realists can be described as believing that the world they study is either objectively real or not, and that they can gain evidence of greater or lesser strength to that effect. The features of the universe that realists study may be unobservable to the unaided senses – exoplanets, black holes, supra molecules, tectonic plates, neural activity, perception, emotion, attitude – and thus to some greater or lesser extent are hypothetical, yet they are considered real, unless evidence shows otherwise (Chakravartty, 2007). For example, theoretical explanations and terms such as aether, phlogiston, animal magnetism, and psychode, once proposed as hypothetical substances, are now not viewed by scientists as being real (e.g., Beloff, 1993). Realists also have theories regarding the existence of and natures of the properties of hypothetical entities, and each is considered to have what is known as a 'truth value': it may be true or false. It is the job of the scientist to devise and conduct research to determine this (Merton, 1973a). Finally, realists believe that it is possible that there are theories that may be true or false regarding the causal forces between the properties of entities. In short, the scientific realist sees "science's unique mission [in terms of] disclosing Truth", and is not perturbed by claims that science is, in fact "subject to all the vicissitudes of conflict, controversy, and contrary interests to which all things social are inherently vulnerable" (Collin, 2017, pp. 456-458). In this sense, then, the working realist assumes that there are objective truths about the universe, and their efforts are directed towards getting at the facts.

Universalism, Mind Independence and Objectivity

For the scientific realist, the assumption that there are universal truths about the world is fundamental: if truth claims are factually correct, they must remain true, regardless of who is observing them (c.f. Merton, 1973a). An archetypal example of this can be found in the world of chemistry, where scientists study porphyrin supra molecules, which include, among others, iron (e.g., hemoglobin), magnesium (e.g., chlorophyll), and cobalt (e.g., vitamin B_{12}) porphyrins. Hawley *et al.* (1998) examine the interactions between tin-based porphyrins and an acid using proton nuclear magnetic resonance (NMR) spectroscopy. The latter approach is necessary, since porphyrins, their chemical properties, and their chemical interactions are not directly observable to the unaided human senses, and so scientists need the assistance of instruments that provide trace evidence on the structure of the supramolecules. Hawley *et al.*'s (1998) study uncovers, for instance, the impact of acid strength on the rate and extent of complex formation, and estimates properties of the complex, such as its apparent association constant. If Hawley *et al.*'s (1998) description of the world they observe via their instruments is correct, then repeated studies of the Hawley *et al.* (1998) kind – seeking to find the impact of acid strength on the rate and extent of complex formation in the specific molecules they are interested in – should converge on a single true value, and should "not vary from person to person or community to community" (Boghossian, 2006, p.13), since the impact is assumed to be universal.

However, the idea of the universality of facts is at odds with constructivism (Merton, 1973a, 1973b), which assumes that "there is a basic fallacy [underpinning the scientific approach] – the supposed distinction … between knowledge and facts" (Bem and de Jong, 2006, p. 130). Bloor (1991, p. 5), for instance, describes knowledge as "whatever people take to be knowledge", and in so doing imposes on knowledge (and so on facts by extension) a lack of universality, since what people take to be knowledge can vary across social groupings, and since knowledge and facts blur into one. As a result, for the constructivist, "universality of objectivity is illusionary" (Sokal, 2008, p. 302), such that the constructivist challenges the presumption that it is possible for chemists such as Hawley *et al.* (1998) to reveal objective truth about the supposed molecules being studied, since "no one arrangement of words is necessarily more objective or accurate in its depiction of the world than any other" (Gergen and Gergen, 2007, p. 462). Rather, the constructivist would view the supramolecules being studied merely as products of historic chemistry scripts and texts, produced as part of a communal tradition. According to this perspective, the tool to measure the unobservable supramolecules, the proton NMR spectrometer, fabricates what might best be described as mythical structures, which become reified by statements (publications in scholarly journals), and which eventually become "part of the tacit skills or material equipment of another laboratory" (Latour and Woolgar, 1986, p. 238), and so enter and perpetuate chemistry discourses.

Beyond the notion of universalism, scientific realists are "committed to the existence of a mind-independent world or reality" (Chakravartty, 2007, p. 9), holding that facts are true regardless of "the knower's cognitive operations and the theoretical, linguistic, or narrative constructions produced by those operations" (Held, 1996, p. 199). For instance, the scientific view of coronal mass ejections is that they are massive releases of gas from the sun, laced with magnetic fields (Howard, 2011). The magnetic properties of these physical objects that are emerging from the sun exist independently of humans' knowledge of them, or humans' reification of them by writing about them in books. Again, constructivism rejects the idea of mind-independence. Instead, the constructivists in these discussions think that "no fact can obtain independently of societies and their contingent needs and interests" (Boghossian, 2006, p. 26). Universalism and mind-independence of facts underpin the notions of objectivity for realists (Boghossian, 2006).

Entity and Theory Realism

What does being a scientific realist look like within marketing, then? The following example uses the notion of brand attitudes to consider this question. First, assume that a marketing researcher posits that "consumers' beliefs regarding the subjective values of certain brand attributes [affect] a brand's overall degree of favorability from a consumer perspective" (Mandler, 2019, p. 660). If the researcher adopts a realist ontology, then the best description of what the researcher is theorizing is:

(i) beliefs regarding brand attributes, and attitudes towards brands, respectively have the real properties of A and F (A = quality perceptions; F = favorability),

(ii) that variance in property A is a cause of variance in property F, and

(iii) that the magnitude of the causal force between A and F is some real value *r*.

Such principles are inherently realist, and a researcher conducting research according to them clearly "ascribes an ontological status to [each]…variable [in the model] in the sense that [they are] assumed to exist independent of measurement" (Borsboom, 2005, p. 58). The unobservable properties (A and F) are assumed to be real conceptual variables, with real conceptual content (quality perceptions and favorability, respectively). Such research also must assume what Borsboom terms theory realism, which is a view that "theories are either true or false" (p. 60). Research conducted according to the principles above—whether at the frontiers of supramolecular chemistry, or of marketing—is attempting to test theory to determine whether it is true or not (Needham, 2018; Hunt, 1991). This is encoded into the very actions taken by the researchers, and their understanding and consequent description of their actions. Such work adopts the assumption that properties (here, beliefs and attitudes) are real (entity realism), and is keen to assess the structural relations of the theory (belief evaluations cause attitude favorability), and so is adopting 'theory realism'.

This observation is critically important. As Chakravartty (2007, p. 31) asserts, "properties and relations are precisely what theories describe": the realist is not only implying the existence of properties, but is theorizing that there is real causal contact between the properties of various objects (Hacking, 1983). In essence, if one is a realist about a theoretical entity or property, then "one must be a realist about at least some aspects of theory also" (Chakravartty, 2007, p. 31). And vice versa. If one accepts "a causal explanation of a given phenomenon, one must accept the reality of the relevant cause" (Chakravartty, 2007, p. 30). Thus, if one believes that A causes F, then one must accept that A and F are real, and that the causal force *r* between A and F is real.

The PLS Approach

Causal Contact or Miracle?

Suppose a realist researcher is interested in studying the causal impact of some hypothetically real unobservable property, A, on another hypothetically real but unobservable property, F. Properties A and F, then, are conceptual variables which, the researcher believes, might exist, and ideally, the researcher would like actual information on A and F's real (co)variances, so as to be able to determine *r*, the magnitude of the causal relationship between A and F (which at this point is a theory the researcher believes could be true). Since A and F are unobservable, information on their (co)variances is missing, but the researcher has data for observable variables *a*1, *a*2 and *a*3, which they believe are of relevance to A, and for observable variables *f*1, *f*2 and *f*3, which they believe are of relevance to F.

The researcher chooses to use PLS to help their cause. PLS constructs X, a composite score (a weighted sum) for A from the observable variables *a*1, *a*2 and *a*3, and constructs Y, a composite score for F from the observable variables *f*1, *f*2, and *f*3. PLS then returns *b*, a number for the relationship between X and Y, and so it seems the researcher has an estimate for *r*.

However, there are serious inconsistencies between how PLS works and the underlying principles of realism. The most worrying is that PLS contains no explicit hypothetical causal link between the unobservable conceptual variables (A and F) and the composites PLS produces (the X and Y). Yet, for the realist, it is imperative that there *is* some sort of hypothesized causal contact between the properties of interest and the tools used to assess the properties: “In order to know that something unobservable exists, one must know the details of at least some of its relations to other things – relations, for example, to instruments of detection” (Chakravartty, 2007, p. 31). In other words, without an explanation of how the unobservable A is causally related to the composite X, there is very little for the realist to hold onto when it comes to believing the claim that variance in X, PLS’s version of conceptual variable A, is somewhat similar to the actual variance in unobservable property A that is hypothesized to exist. The realist believes that there is a true way that property A varies and covaries, and *many* ways that it does *not* vary and covary, and a necessary (albeit not sufficient) step in becoming confident that X’s variance and covariances mirror those of property A is that there *must be a theory* of how the real property A and composite variable X are related.

PLS does not contain such a theory – there is no explicit recognition of causal contact between property A and X possible in a model of its kind: no formal correspondence between observable variables *a*1, *a*2, *a*3 and property A, or between X and property A. By way of explanation, Figure 1a presents a realist variable framework, which has implications for the realist’s view on measurement. Thus, Figure 1a shows the realist’s theory of how conceptual variables might exist and covary, and a theory of how those conceptual variables might causally act on potential instruments of measurement. While Figure 1a is consistent with certain aspects of Bagozzi’s (1984, p. 12) version of holistic construal, which he claims is an essentially “realist theory of science”, the realist variable framework stands on its own, whether or not holistic construal is commensurate with it. For the realist, then, the following explicit theories can be either true or false:

Figure 1

(i) A theory that there exist real but unobservable conceptual variables, with A and F being the main conceptual variables of interest to the researcher, and with numerous other conceptual variables (the *u*s) also posited to exist. The D_A and D_F are "Sentences specifying the meaning of A [and] F" (Bagozzi and Yi, 2012, p. 12), such that each D term explains "what it is" that each variable is (Bagozzi, 1984, p. 20). The sentences are useful because they identify the existential commitments the realist is making with respect to the conceptual variable, outlining what it means for the conceptual variable to have real existence and vary if, indeed, it has real existence. Not all conceptual variables are understood well enough to be ascribed a D term.

(ii) A theory that variance in A is a cause of variance in F. The causal contact between A and F is represented with the dashed arrow, and its valence and magnitude are indicated with *r*. For the realist in this example, it is the relationship *r* that is of key interest.

(iii) A theory that A and F are causes of the variances in observable variables *a*1, *a*2 and *a*3, and in the observable variables *f*1, *f*2 and *f*3, respectively. Realists require a theory of causal contact between the unobservable conceptual variables and the observable data, and Figure 1a models the causal contacts as solid arrows from property A and from property F to their respective *a* and *f* items.

(iv) Finally, the realist has a theory about the other causes of the variances in the *a*s (*u*1, *u*2, *u*3), the *f*s (*u*4, *u*5 and *u*6) and in property F (*u*7). Again, the solid arrows from the *u*s to the *a*s and the *f*s, and the dashed arrow from *u*7 to property F represent the necessary causal connections, and the signs and magnitudes of the causal contacts are represented with the *q*s.

Figure 1a, therefore, presents the realists' hypothesized causal contacts between hypothetical properties of entities and data that could be observable. The theoretical claims about the causal contacts between unobservable conceptual variable A and observable variables *a*1, *a*2, and *a*3, and between unobservable conceptual variable F and observable variables *f*1, *f*2 and *f*3, amount to hypothetical *data generating mechanisms* (Markus and Borsboom, 2013). That is, A and F, as well as the causal impacts of the unobservable *u* variables on the observable data, are unobservable but real data generating mechanisms, explaining the variances in the observable *a*s and *f*s.

Importantly, as Borsboom (2005, p. 107) observes, "if we aim to construct a measuring instrument that measures a single attribute with a number of observed variables, we will build a structure that strongly resembles a latent variable model". Thus, Figure 1a's data generating mechanisms make claims that could be *tested* with empirical data, using latent variable analysis (Borsboom *et al.*, 2003), and perhaps employing a common cause / common factor-based structural equation model (SEM) methodological approach (Haig, 2018). Here, Figure 1a's ontological commitment is that conceptual variable A is a common cause of (or, to use a different moniker, common factor causing) variances in observable items *a*1, *a*2, and *a*3, and that latent variable F is a common cause of (or common factor causing) variances in observable items *f*1, *f*2, and *f*3. Clearly, if one subscribes to realism, then the realist variable framework (Figure 1a), in which unobservable and observable variables are causally linked, looks similar to the 'common factor analysis' model that many analysts use. The latter is not surprising since the realist variable framework commits to the possibility that the common causes (the common factors driving the analyst's model) of the *a*s and the *f*s literally *are* A and F, the conceptual variables that are the focal entities of the analyst's interest (Haig, 2018): if one subscribes to realism, then the common factor model maps over the realist's conceptual model, in which unobservable and observable variables are causally linked.

Various antirealist alternatives to Figure 1a are presented in the literature. For instance, Rigdon (2012, p. 347) describes the "Concept Proxy Framework" (CPF), which adds into holistic construal an additional conceptual variable that is quite different to the realist's focal conceptual variable of interest (see Figure 1b). That is, Rigdon (2012, p. 344) asserts that "within the Holistic Construal… in the middle is understood to be a common factor". For Rigdon, common factors are different from, and additional to, the focal conceptual variables that exist in Figure 1a. In this way, Rigdon's CPF, "an alternative measurement framework", contains a conceptual variable *and* a common factor (labelled a "proxy" variable), such that the proxy variable "lies between concept and indicator" (Rigdon, 2012, p. 347).

Significantly, CPF provides no explanation of the proxy variable's causal contact with the conceptual variable it is meant to be a proxy of, and avoids the language of causality when it comes to discussing the proxy variable's relationship with observed data. CPF's stance, when it comes to causal claims, appears to be that the focal conceptual variables *do not* emit causal forces that act on observable data. Rigdon (2012, p. 348) argues that "The theoretical concept remains idealized and out of reach", and later expositions (Rigdon *et al*., 2019) emphasize this stance. CPF, then, places conceptual variables 'outside' of a common cause model, essentially "denying that one can have knowledge of the unobservable" (Chakravartty, 2007, p. 12), and claims that conceptual variables exist only in some undefined relation to proxy variables (common factors), not observable data (measures). On this front, CPF is incompatible with scientific realism, which explicitly maintains that unobservable conceptual variables *can* causally impact their observable measures (Borsboom, 2005), allowing the realist the prospect of generating knowledge of unobservables. Rather, CPF seems similar to constructive empiricism, a strand of antirealism that accepts that unobservable variables could exist, but that refutes that one can ever have knowledge of them (Chakravartty, 2007).

While Figure 1b contains two unobservable conceptual variable blocks, in its original form (Rigdon, 2012, p. 347), it contains only one unobservable conceptual variable. Accordingly, CPF is largely silent in terms of specifying whether unobservable conceptual variables cause each other, or whether proxy variables cause each other, and so does not provide the realist with the "sort of structures [they] are after" (Chakravartty, 2007, p. 39). Indeed, the "concept of structure required by the realist is one that is tied to specific kinds of [properties of particulars] and their characteristic relations" (Chakravartty, 2007, p. 40). Causal contacts between conceptual variables, and between conceptual variables and means of detection, are fundamental to the realist approach. These broad observations regarding CPF are particularly helpful later when addressing PLS in the context of interpretational confounding and factor indeterminacy.

Despite CPF's lack of utility for the realist researcher, the latter may still wonder whether PLS is a viable tool that would enable them to measure their conceptual variables and test their theory regarding the inter-relationships between conceptual variables. Figure 1c presents the PLS approach, and given that the researcher is still a realist:

(v) They have a theory that there exist real but unobservable conceptual variables, properties of objects, A and F, with theoretical definitions D_A and D_F respectively.

(vi) They also theorize that A and F are causally related, magnitude *r*, again represented with the dashed arrow.

(vii) However, when PLS is used by the realist researcher, the theorizing stops here. Indeed, for PLS, these theories (v and vi) are superfluous (optional), and play no role in its mechanisms.

(viii) Rather, in PLS, the observable variables *a*1, *a*2, and *a*3 are combined into a weighted composite to construct variable X, and observable variables *f*1, *f*2 and *f*3 are combined into a weighted composite to construct variable Y. The algorithms that PLS uses do not map onto any hypothesized causal contact between the property A and *a*1, *a*2 or *a*3, and the property F and *f*1, *f*2 or *f*3, and properties A and F play no explicit hypothetical causal role in PLS's construction of the weighted composites X and Y.

(ix) As such, when PLS presents a number called *b*, the empirical relationship between X and Y, there is no theory of causal contact between the *b* PLS provides and the *r* the *b* is meant to provide information on, and thus no necessary relationship between *r* and *b*.

While one kind of PLS advocate may describe "PLS path modeling as [one of several] methods for constructing empirical approximations to underlying constructs" (Rigdon, 2012, p. 346), or claim that "conceptual variables are … crucially important to PLS path modeling" (Rigdon, 2016, p. 602), the realist should be skeptical about such claims, because the PLS model contains no causal contact between unobservable conceptual variables and data, and thus no way of testing whether or not the data could provide a viable representation of unobservable variables. The realist would be more comfortable subscribing to the observation that the X that PLS constructs is best understood as "an artifact… a human-made object" (Hair *et al*., 2019, p. 569). To be less skeptical of PLS's claim that X is an actual *measure* of property A, the realist needs the causal contact between *a*1, *a*2, and *a*3 and property A to be explicit in the model used. Without the latter, PLS's claim that X measures property A is simply presented as a "brute fact, that cannot be explained" (Kim, 2010, p. 71), and falls foul of Putnam's (1979, p. 73) no-miracles argument which asserts that "realism is the only philosophy that doesn't make the success of science a miracle". Specifically, stating that X measures A, but failing to demonstrate how X *could be* a measure of A, requires that one fall back on a miracle as the explanatory source for X's measurement capability.

As Edwards (2014, pp. 26-28) puts it: "To take something to be 'primitive' is to hold that there is no explanation of its nature forthcoming [in Putnam's terms, it is a miracle]… more powerful theories…leave fewer things as primitive,… the number of primitives a theory takes should better be as low as possible. This is one dimension along which theories can be compared". When the realist uses PLS to measure unobservable properties, then, they are relying on measurement-as-a-miracle assumptions and, rather than minimizing the number of primitives they take on, they are accepting a proliferation of primitives in their theoretical models. Ultimately, PLS's miracle of measurement also means that there is no theoretically-derived causal link between the *b* that PLS returns and the *r* the realist wants to know, and so if *b* is saying anything meaningful about *r*, then that too must be a miracle. Faced with the option of accepting a primitive fact of this kind, or of rejecting the claim that X and Y measure properties A and F, and so of rejecting the idea that *b* says something about *r*, the realist will choose the latter, since they always prefer to "choose common sense over miracles" Chakravartty (2007, p. 4).[4]

[4] CPF also appears to rely on a miracle argument, if the realist is to believe that the observable variables measure unobservables.

PLS: The Weighting Process Constructs Empirical Meaning

Where does X get its empirical meaning from if it is not from property A? The answer to this question requires an understanding of how PLS aligns with constructivism, and in particular, two features PLS shares with the constructivist tool kit: non-universality, and the mind-dependence of facts. This argument is not entirely novel, but its implications remain underexplored for realists. For example, Henseler (2017) identifies composite approaches (such as PLS) as being constructivist, located in a world where researchers modeling with a "composite can be thought of as designers: They design this construct", explicitly mixing up "ingredients … [and arranging them] to form a new entity" (p. 180), rather than explicitly attempting to measure unobservable variables that "exist in nature" (Henseler, 2017, p. 178). This constructivist interpretation has seriously problematic implications for realists who wish to measure real unobservables, and the method used by PLS to construct values for X and Y makes it particularly pernicious in this regard.

Figure 2 outlines the various steps PLS uses to form composites in a simple model with two core variables, X and Y, and shows the progression of empirical meanings in X and Y that take place as PLS moves through its iterations (e.g., see Haenlein and Kaplan, 2004; Rönkkö *et al.*, 2016).

Figure 2

1. First, in iteration n=0, PLS creates X_0, a composite[5] of *a*1, *a*2, and *a*3 using unit weights.

   Eq 1: $X_0 = a1 + a2 + a3$

   Similarly, PLS creates Y_0, a composite of *f*1, *f*2, and *f*3 using unit weights.

   Eq 2: $Y_0 = f1 + f2 + f3$

   Given that X is not a directly observable variable (it is unobservable), and that "The 'empirical' meaning of an unobserved variable derives from its relations to one or more observed variables" (Burt, 1976, p. 6), composites X_0 and Y_0 get their empirical meanings from the *a*s and the *f*s.

2. In iteration n=1, PLS calculates the relationships between *a*1, *a*2, *a*3 and Y_0[6], either using correlations (called *Mode A*), or using regression coefficients (called *Mode B*). These relationships become the weights that are used to create a new X variable (X_1). For instance, if the relationship between *a*1 and Y_0 is .90, between *a*2 and Y_0 is .20, and between *a*3 and Y_0 is .01, X_1 is calculated as:

[5] Regardless of what some PLS users wish or claim in their diagrams (e.g., Henseler *et al.*, 2014), PLS *only* creates composites "because PLS path modeling cannot do anything else" (Rigdon, 2016, p. 600): PLS "treats all indicators as composite indicators that jointly define the construct under consideration" (Hair *et al.*, 2019, p. 569).

[6] Models with more than two composites use a weighted sum of all composites that are linked to X by a regression path. There are various different ways this step, called inner estimation, can be done, but we ignore them for simplicity because they all produce the same results for a two-composite model, and any differences in more complex models are irrelevant to our point.

Eq 3: $X_1 = .90{*}a1 + .20{*}a2 + .01{*}a3$

Similarly, PLS calculates the relationships between *f*1, *f*2, *f*3 and X_0, and these relationships become the weights that are used to create a new Y variable (Y_1). For instance, if the relationship between *f*1 and X_0 is .80, between *f*2 and X_0 is .15, and between *f*3 and X_0 is .02, Y_1 is calculated as:

Eq 4: $Y_1 = .80{*}f1 + .15{*}f2 + .02{*}f3$

Importantly, item weightings assign empirical meaning to composites (Burt, 1976; Bagozzi, 1984; Wilcox *et al.*, 2008). Thus, the empirical meanings of X_1 and Y_1 are potentially different to the empirical meanings of the original X_0 and Y_0.

3. PLS then examines the change in the scores produced by the new and old X ($\Delta_n X$) and the new and old Y ($\Delta_n Y$), and asks 'do the new X and Y variables have the same empirical meanings as the old X and Y scores?'

4. If the answer is no, PLS goes through a second iteration (n=2). It calculates the relationships between *a*1, *a*2, *a*3 and Y_1, and creates a new X variable (X_2) using the new relationships between the *a*s and Y_1 as weighting values. Likewise, it calculates the relationships between *f*1, *f*2, *f*3 and X_1 and creates a new Y variable (Y_2) using the new relationships between the *f*s and X_1 as weighting values.

5. The process of repeating iterations continues until the empirical meanings of the new versions of X and Y do not change from iteration n-1 to iteration n. At this stage, the final empirical meanings of X and Y are Xn and Yn respectively.

Clearly, the PLS process changes the original empirical meaning of X using the changing empirical meanings of Y, and vice versa. If *a*1, *a*2, and *a*3 were placed in a model that did not contain *f*1, *f*2 and *f*3, but contained a different set of observable items (say, *f*4, *f*5, and *f*6), the empirical meaning of X would not be the same as that obtained when it was included in a model containing *f*1, *f*2 and *f*3. More generally, in models containing many composites, the empirical meaning a composite, C, is given by PLS (and hence its variance and covariances with other composite variables) is partially determined by the indicators of the *other* composites that composite C is linked to in the model. This process is unsatisfactory for the realist, who would wish the empirical meaning of X to be determined by A.

Are PLS Weightings Really a Problem for Realists?

Some might challenge the conclusion that PLS's weighting procedures are uniquely problematic for the realist. Three such challenges are examined here.

First, the model-dependent nature of PLS weighting shares much in common with what is known as interpretational confounding, which refers to inconsistency between empirical and conceptual meanings of a variable (Burt, 1976; Howell *et al.*, 2007). In common cause (i.e. common factor) analysis models, interpretational confounding occurs when "there are few reflective indicators …or the epistemic relationships of …indicators to …associated construct[s] are weak relative to structural parameters in a structural equation model"

(Howell *et al.*, 2007, pp.207-208). Inferences from such models "become ambiguous and need not be consistent across separate models" (Burt, 1976, p. 4). This situation recalls the well-established problem of factor indeterminacy (Mulaik, 2009), where "the common and unique factor scores in the common factor model are not uniquely determined by the observed variables" (McDonald and Mulaik, 1979, p. 297). However, while interpretational confounding *is* a significant problem when testing models, factor indeterminacy does *not* affect the assessment of common cause model fit (although it does have other problematic implications), such that "theory testing via [common cause] models remains a viable research strategy in spite of factor indeterminacy" (Bentler, 1980, p. 442).

It seems that for the realist looking to measure A and F and assess *r*, common cause modelling is a viable option (despite being subject to factor indeterminacy), whereas PLS will always be problematic due to its inherent interpretational confounding problems, whereby the empirical meanings of the X and Y composites, and the construction of its *b* value (the relationship between X and Y), will vary as a result of the empirical model the researcher locates the composites within.

Rigdon *et al.* (2019), however, building on the picture provided by CPF, argue that common cause models have an *additional* factor indeterminacy issue on top of the one noted above, and claim that this new factor indeterminacy issue *does* invalidate theory testing with common cause models. Recall that unlike the realist variable framework, CPF asserts that a common factor is not the same thing as the researcher's focal conceptual variable, but is a different variable that sits *between* the conceptual variable and its measures. For Rigdon *et al.* (2019), the common factor model is not a model in which a conceptual variable causes variance in its measures – the conceptual variable sits outside of the common factor model altogether. Accordingly, Rigdon *et al.* (2019) conclude that there is an *out-of-model relationship* between the common factor and the conceptual variable, and extend the argument to content that: (i) out-of-model relationships are biased by indeterminacy, which "substantially diminishe[s]" the meaningfulness of the common factor model in terms of representing its conceptual variable, meaning that (ii) common factor variables are "a crucial threat to validity" in measurement (p. 436). Based on logics of this kind, perhaps, Rigdon (2016, p. 604) defends PLS, stating that "there seems no basis for arguing that [common] factor proxies will have any overall advantage over composite proxies".

However, CPF is inconsistent with realism. Realism explicitly maintains that unobservable conceptual variables definitely *do* have causal impacts on their measures: "the only thing all measurement procedures have in common is either the implicit or explicit assumption that there is an attribute out there that, somewhere in the long and complicated chain of events leading up to the measurement outcome, is determining what values the measures will take" (Borsboom, 2005, p. 153). For the realist, assumptions regarding the reality of causal paths from conceptual variables to observable variables are central to the ontological stance: the conceptual variable is the hub of the model, and does not stand outside of it. Accordingly, Rigdon *et al.*'s (2019 p. 436) core claim concerning the common factor model that "the conceptual variable stands outside the model" is disputed by the realist, as is the subsequent announcement that "factor indeterminacy induces uncertainty around the relationship between the common factor and the conceptual variable". Realists, at least, can dispense with assertions that common cause modeling approaches are inherently as problematic as PLS's weighting problems with respect to interpretational confounding, or that PLS's weighting problems are overstated.

Second, some may reason that the model-dependent nature of PLS's composite weighting is a problem only when there is model misspecification. For example, Schuberth *et al.* (2018) argue that for a composite, if the between-block correlations follow an inter-battery factor model, and this is the case for all composites simultaneously, then the weights should not vary depending on how the inner model is specified (in large samples at least)[7]. However, a realist should not be satisfied with such a solution, which cleaves too close to instrumentalism or pragmatism. Consider the practicalities. How should the realist ascertain whether the model is correctly specified? A common factor model would appear to be the method of choice here, unless the realist wishes to rely on a miracle-of-measurement assumption. Undertaking common factor analysis to decide on the makeup of one's PLS model—in the expectation that PLS's resulting composites will maintain the empirical meaning of those common factors—papers over the realist's concerns: (i) PLS's composites have no hypothetical causal contact with conceptual variables, and thus (ii) analysis based on PLS composites can have no truth value (cannot be either true or false) with respect to representing or describing some existent property. Ignoring realists' worries regarding the model-dependent nature of PLS composite weightings based on *a priori* assumptions regarding the correctness of the item banks overlooks the core ontological criticisms of PLS from a realist perspective, in favor of instrumentalist or pragmatist views, which dismiss the realists' ontological claims.

Third, it might be argued that realists' concerns are nullified by the use of consistent PLS (PLSc) and its variants, which appear to integrate common factors into PLS. However, PLSc's use of common factors does not elevate PLS to a method that meets the realist's

[7] Mikko Rönkkö suggested this line of argumentation.

aspirations for hypothetical causal contact between conceptual variables of interest and observable data. In PLSc, common factors are employed to calculate a 'reliability index' (ρ_A) for each composite, and the ρ_A are used to change the inter-composite relationships obtained in the course of regular PLS analysis (Dijkstra and Henseler, 2015). For instance, in Figure 1c, the PLSc approach would (i) calculate an inter-composite relationship *b* using the composites X and Y obtained from the process outlined in Figure 2, (ii) calculate ρ_A for X (ρ_AX) and ρ_A for Y (ρ_AY), and then (iii) calculate *B*, a 'consistent' version of *b*, by dividing *b* by $\sqrt{(\rho_A X * \rho_A Y)}$, such that *B* 'corrects *b* for attenuation'.

Unfortunately, for the realist, PLSc maintains the lack of causal contact between the unobserved conceptual variables A and F and the *a*1, *a*2, *a*3, and *f*1, *f*2, *f*3 in Figure 1c, and dividing *b*, the observed relationship between X and Y, by some denominator does little to pacify the realist's concerns on this front.[8] Given that, as Hair *et al.* (2020, p. 103) put it, in PLS, "an estimated composite always depends on the nomological network", it follows that the relationships between composites that PLS calculates for its models are *always* dependent on what else is being studied in the model, and realists are left unsatisfied with the supposed 'remedy' PLSc offers.

The Non-Universal and Mind-Dependent Nature of PLS Output

As shown above, the composites and inter-composite relationships that PLS constructs are essentially non-universal: (i) they are not causally connected to hypothetically real conceptual variables, (ii) they are the product of the choices that research groups and individuals make

[8] Further, PLSc constrains the common factor "loadings to be proportional to PLS weights" (Rönkkö *et al.*, 2016, p.21): thus, ρ_AX and ρ_AY are themselves model dependent, shaped by the final weightings produced in Figure 2.

regarding the set of composites and items to enter into a PLS analysis, and (iii) they are the product of the location of those composites with respect to each other. Different social groups, in different places, at different times, will make different choices, show interest in certain matters, retain certain ideas, and because "members of a knowledge-seeking group may have certain political and social values … those values may influence how they conduct their work—what observations they make" (Boghossian, 2006, p. 20). Accordingly, the features of the world driving the output of PLS are fundamentally social in nature, and so the outputs that PLS produces are, by design, non-universal and subjective: for the realist, the latter stand far from their scientific aspiration of objectivity (Merton, 1973a).

A constructivist might argue that what PLS does is no worse than realists' scientific tools, claiming that realist's notions of objectivity are illusionary and unachievable, that *all* scientists' instruments and models are socially constructed, and thus non-universal. However, the realist cannot condone PLS just because of claims that other methodologies have problems of one kind or another. The realists' approach to science *aspires* to objectivity, and since PLS proposes no underlying theory of causal contact *at all* between theoretical variables and observable data, PLS does not share this aspiration. PLS's non-universality is deeply embedded in its mechanisms, placing it at odds with the intentions of realists who may use it in practice.

But to a constructivist, PLS's non-universality is not problematic because constructivism holds that "all facts are socially constructed" (Boghossian, 2006, p. 22), and this thinking shades into the further appeal that "there are many radically different yet 'equally valid' ways of knowing the world, with science [and scientific facts] being just one of them" (Boghossian, 2006, p. 23). Thus, PLS's non-universality frees the empirical constructivist from the shackles of using methodologies that aspire to identify universal scientific facts and truth. Instead, PLS produces its own constructed accounts of the world, that vary from model to model. Henseler (2017), for instance, embraces this constructivism, likening the composites that PLS produces to Nelson and Stolterman's notion of the design of artifacts. Specifically, Nelson and Stolterman (2012) describe the world in archetypally constructivist terms: for instance, they claim that "[h]umans did not discover fire – they designed it" (p. 11), and thus that "scientists … can be understood more as design critics than natural scientists" (p. 27). By linking PLS's approach to the design notion of Nelson and Stolterman, Henseler (2017) locates PLS in the realm of critical design, where PLS users essentially "imagine that-which-does-not-yet-exist, to make it appear" (Nelson and Stolterman, 2012, p. 12).

PLS outputs also align with constructivism since, as Borsboom (2005) notes, the outputs of composite-based analyses are not mind-independent: they exist only because they have been constructed by the researcher. A realist has no reason to expect the outputs of PLS to refer to any factually-existent features of the world. Take Benitez *et al.*'s (2018) 'IT infrastructure flexibility' variable, a weighted composite constructed from four other composites: IT compatibility, IT connectivity, modularity, and IT personnel skills flexibility. For the realist to get meaning from the work, the questions that require answering include 'what is the existential nature of the composite that is created and labeled IT infrastructure flexibility?', and 'where is the causal contact between it and a hypothetically real IT infrastructure flexibility conceptual variable?' The concerned realist may feel justified in dismissing the composites PLS constructs because of lack of evidence that the composites stand for conceptual variables that really exist in nature, not simply on paper or in the discussions of the research team: the realist needs evidence that PLS's constructed variables are really 'out there', in the world of facts.

Constructivists have no such concerns: for them, it is sufficient that there is a narrative that says that PLS constructs composites, and that there are relationships between the latter. Lack of causal contact with the realists' properties is not a constraint. Constructivists have no ontological imperative that the outputs of analyses be mind-independent, or dependent on properties that exist in reality, separately from the community that creates them: quite the opposite. Thus, PLS emerges as a constructivist device for "the reification of theories and practices… [one of several] marketed forms of these reifications" (Latour and Woolgar, 1986, p. 68), consolidated with "the art of persuasion… [enabling the constructivist] to convince others that … what they say is true" (p. 69). In short, PLS fits the constructivist notion of science, which sees science's factual objectivity, "[its] 'out-there-ness' [as] the consequence of scientific work rather than its cause" (Latour and Woolgar, 1986, p. 182).

Discussion and Conclusions

By any reasonable standard, PLS fails the test as a useful tool for realist scientists because it cannot model theories of causal contact between observable data and theoretical entities. A problem arises, therefore, if users of PLS assume that PLS has a theory of causal contact built into it. The problem is exacerbated when PLS advocates imply that causal contact *is* a feature of the method by, for instance, using the term measurement (e.g., Hair *et al.*, 2019) to refer to PLS composites. Accordingly, it appears that some realist marketing researchers using PLS are adopting *accidental constructivism*, and in so doing, are producing research that fails the realist litmus test. PLS can *only* engage in constructivism, a place that leaves the scientific realist "with no knowledge that could be called 'true' [emerging from it]" (Pennock, 2019, p. 210).

Indeed, rather like Cargo Cult Science (Feynman, 1974), for the realist, although from the outside PLS may look like it "follow[s] all the apparent precepts and forms of scientific investigation, [it is] missing something essential" (p. 11), and when one examines PLS, one realizes that this "something essential" is formal causal contact with theoretical entities and theories. Feynman's (1974) notion of scientific integrity demands that the scientific realist engage in "a kind of leaning over backwards" (p. 11), which Pennock (2019, p. 37) translates as being "an ideal", and for the realist, that ideal is the underlying foundation of causal contact that PLS is missing. This notion of the ideal "will be very difficult" to achieve but, under the realist worldview, to seek it is a "central scientific character virtue" (Pennock, 2019, p. 37), and to ignore or skip over PLS's inherent lack of causal contact between theoretical entities and observable data, as though it is a minor matter that can be ignored, stands at odds with the purpose of science.[9] And yet, PLS remains very popular in many marketing journals. We see three potential reasons for this:

(1) Many practicing researchers lack an understanding of what PLS does, and how it differs from common cause SEM, a methodology that realists are often comfortable with. Relatedly,

[9] PLS has other problems. (1) It is often claimed that PLS's weighted composite scores are more reliable than equal weight composites, despite evidence showing that even in favorable cases, the difference is in the third decimal (McIntosh *et al.*, 2014). (2) Regarding the reference distribution used for calculating the p values after bootstrapping: Henseler *et al.* (2009, p. 305) claim the test-statistic follows the t-distribution with df=m+n–2, where n is the number of bootstrap samples and m=1, while Hair *et al.* (2014, p.134) state that the degrees of freedom are n–1, where n is the sample size. Neither claim is supported by evidence, and both are contradicted by simulations showing that PLS estimates are often non-normal and so standard errors cannot follow t (Rönkkö and Evermann, 2013; Goodhue *et al.*, 2007). (3) Some argue that before the p-value is calculated from bootstrapping, the bootstrap replications should be replaced by their absolute values, or their negatives (called sign-change corrections). However, Rönkkö *et al.* (2015) show that the idea of sign-change corrections is at odds with the theory behind bootstrapping.

some may assume that, although some tools may be better than others, the fact that PLS is available must mean that it is at least somewhat good. Criticisms of PLS may be shrugged off, compartmentalized as technical issues that are fixable: even if PLS's competitors offer "superior alternatives" (Rönkkö *et al.*, 2016, p. 24), PLS might be deemed good enough. Thus, even in the presence of potentially well-reasoned calls for scientific realists to abandon PLS, the latter may fail to see PLS as being absolutely unfit for realists' purposes, and Pennock's (2019, p. 144) warning, that "[w]hen instruments malfunction, scientific progress is retarded", is ignored.

These matters go hand-in-hand with precedence, the deference to so-called authority figures evident in many fields, not least marketing. Guide and Ketokivi (2015, p. vii) advise that authors "should always avoid rhetoric such as 'expert X has suggested that estimator Y be used.' Such rhetorical appeals must be replaced with methodological justification". Yet, for some realists, it may be justification enough that a senior or well-known authority figure uses PLS: in the latter case, that researcher may reason that PLS must be a valid method by mere association.

(2) Some researchers may approach the world from anti-realist stances other than constructivism. For example, "the instrumentalist movement … involves a cluster of views… characterizing … scientific discourse about the unobservable [as] merely an instrument for making predictions concerning the observable" (Rowbottom, 2018, p. 84). The hypothetical entities and properties that these theories contain are not deemed objectively real, since instrumentalists only include observable phenomena in their lists of things that really exist. Accordingly, instrumentalism does not share realism's demand for a theory of causal contact between hypothetical variables and instruments of detection. A PLS advocate might be

tempted to argue that since realists' criticisms of PLS are irrelevant for instrumentalists, PLS might be considered a part of the instrumentalist marketers' tool kit. However, instrumentalists may have other problems with PLS, since they *do* subscribe to a mind independent reality: that reality only contains *observable phenomena*, and center stage to this stance, then, is the prediction of these visible events (Chakravartty, 2007). Yet, PLS's core design feature capitalizes in a strong way on mind dependence, such that PLS only constructs new variables, and does not model variables that exist in nature. Specifically, PLS creates weighted composites, and the challenge for the instrumentalist lies in matching the weighted composites' empirical meanings with real observable phenomena. If PLS struggles with the latter, it becomes of little use to the instrumentalist. Further research is needed to examine whether PLS has a legitimate place in the instrumentalists' toolkit.

(3) Finally, some researchers claim that pragmatism underpins PLS and other composite modeling approaches (e.g., Chin, 2010; Henseler *et al.*, 2016; Schuberth *et al.*, 2018). Some strands of pragmatism might be compatible with realism (e.g., pragmatic realism – see Massimi, 2018), others are not. As Rowbottom (2018, p. 93) explains, "being a pragmatist aligns well with being an instrumentalist about science… Indeed, some forms of instrumentalism about science may be construed as local forms of pragmatism". Unfortunately, it is not clear which strand of the "family of views belonging to the tradition of pragmatism" (Chakravartty, 2007, p. 13) is being referred to by those who argue for a pragmatist view of PLS, or whether their claims are well-grounded. Classic pragmatism focuses on the practical consequences of scientific endeavor, and science's "actual or possible empirical observations, scientific predictions, and heuristic uses in problem solving, where claims are conceived as a basis for action" (Chakravartty, 2017, p. 14). Thus, pragmatism prioritizes the use of science to solve problems, rather than discover the objective

truth of the world for its own sake, and considers the truth of scientific statements to be defined mainly by whether or not such statements allow useful interventions (Hacking, 1983). From this perspective, PLS should be judged by its usefulness outside of the context of a team of researchers doing some data analysis (i.e. that a team of researchers find it useful to use PLS is not, in itself, evidence of PLS's usefulness to the world outside of the research team): it should produce findings that are useful to audiences *beyond* the research team – demonstrating an ability to solve problems in the observable world. It is incumbent on PLS researchers claiming to adopt pragmatism to demonstrate that the technique and their research *is* pragmatic: simply claiming that PLS is used for pragmatic purposes is not enough. Such tasks are rarely attempted in typical PLS studies in marketing and related fields, which almost always concentrate on explaining aggregate patterns in existing data sets, which rather weakens claims that PLS is often being used in a pragmatic fashion. Thus, future research is needed to examine whether PLS has a legitimate place in pragmatists' toolkits, although it seems likely that the challenge instrumentalists face—matching the empirical meanings of the weighted composites PLS produces with real observable phenomena—will exist for the pragmatist PLS user also.

Despite the problems of PLS for realist research, and likely problems for instrumentalists and pragmatists, constructivists can take heart with the results of the analysis above, finding aspects of PLS's antirealism rather appealing. PLS provides a tool that does not require the empirical constructivist to commit to any theory regarding the reality of conceptual variables, or their causal contacts with anything. The constructivist should have no problem with the idea that applications of PLS to the same data set, but with different contextual settings (i.e., different nomological nets), can result in different composites, and different inter-composite relationships. For the realist, the latter fatally undermines PLS's validity as a method to provide any evidence for even the most tentative conclusions regarding universal, mind-independent facts about reality. The constructivist, however, contends that there are "many equally valid ways of knowing the World" (Boghossian, 2006, p. 1). PLS allows, even encourages, the constructivist to seek out these multiple 'truths'. The findings that scientific realist methodologies produce can be compartmentalized by constructivists, ignored even, and labelled as only *one route* to knowledge, *one kind* of fact. Seen in this light then, PLS provides a potential route for constructivist researchers to "rationally arrive at opposed conclusions, even as they acknowledge all the same data" (Boghossian, 2006, p. 59).

An overall conclusion, then, is that the outputs that PLS produces lie outside the scope of realist inquiry, but are potentially aligned with constructivism's dictums. Clearly, these insights have significant implications for (a) how realist research communities process published studies that employ PLS, and (b) the choice of analysis tools realist research communities adopt moving forward. Certainly, when examined through the lens of realism, it is hard to see how PLS's outputs correspond to real properties of features of the world, and so realist researchers may decide that they need to reappraise the validity of claims made in PLS research studies. Of course, researchers of all ontological stripes should examine the analysis tools that are in their 'toolboxes', to determine the fit of those tools with their chosen ontology, but specifically in the case of realist researchers, they should check *any* tool that they may be considering using, to establish its correspondence with their commitments regarding the reality of the conceptual variables and causal forces in their theories. For instance, special attention should be paid to all methodologies that create composites, to determine the extent to which they align with scientific realism vis-à-vis antirealist ontologies. While no method that we know of (and that is feasible for social science) is without flaws in this regard, there are methods which at least explicitly propose data generating mechanisms, and which when used appropriately can 'test' the mechanisms against observable data. Those whose worldviews align with scientific realism should be consciously aspirational in their work, and thus use the method which provides the strongest feasible test of their theory (Feynman, 1974). For the realist at least, this should not be PLS.

References

Antonakis, J., Bendahan, S., Jacquart, P. and Lalive, R. (2010), "On making causal claims: a review and recommendations", *The Leadership Quarterly,* Vol. 21 No. 6, pp.1086-1120.

Bagozzi, R.P. (1984), "A prospectus for theory construction in marketing", *Journal of Marketing*, Vol. 48 No. 1, pp.11-29.

Bagozzi, .P. and Yi, Y. (2012), "Specification, evaluation, and interpretation of structural equation models", *Journal of the Academy of Marketing Science*, Vol. 40 No. 1, pp.8-34.

Beloff, J. (1993), *Parapsychology: A Concise History*. The Athlone Press, London.

Bem, S. and de Jong, H.L. (2006), *Theoretical Issues in Psychology: An Introduction*. Sage Publications, London.

Benitez, J., Ray, G. and Henseler, J. (2018), "Impact of information technology infrastructure flexibility on mergers and acquisitions", *MIS Quarterly*, Vol. 42 No. 1, pp.25-43.

Bentler, P.M. (1980), "Multivariate analysis with latent variables: causal modeling", *Annual Review of Psychology*, Vol. 31, pp.419-456.

Bloor, D. (1991), *Knowledge and Social Imagery.* 2nd Edition. The University of Chicago Press, Chicago.

Boghossian, P.A. (2006), *Fear of Knowledge: Against Relativism and Constructivism*. Oxford University Press, Oxford.

Boghossian, P. (2012), "Critical thinking and constructivism: mambo dog fish to the banana patch", *Journal of Philosophy of Education*, Vol. 46 No. 1, pp.73-84.

Borsboom, D. (2005), *Measuring the Mind: Conceptual Issues in Contemporary Psychometrics*. Cambridge University Press, Cambridge.

Borsboom, D., Mellenbergh, G.J. and van Heerden, J. (2003), "The theoretical status of latent variables", *Psychological Review*, Vol. 110 No. 2, pp.203-219.

Burr, V. (2015), *Social Constructionism.* 3rd edition, Routledge, London.

Burt, R.S. (1976), "Interpretational confounding of unobserved variables in structural equation models", *Sociological Methods & Research*, Vol. 5 No. 3, pp.3-52.

Chakravartty, A. (2007), *A Metaphysics for Scientific Realism: Knowing the Unobservable.* Cambridge University Press, Cambridge.

Chakravartty, A. (2017), *Scientific Ontology*. Oxford University Press, Oxford, UK.

Chin, W.W. (2010), "How to write up and report pls analyses", Vinzi, V.E., Chin, W.W., Henseler, J. and Wang, H. (Ed.s), *Handbook of Partial Least Squares: Concepts, Methods and Applications*. Springer, London, pp.655-690.

Collin, F. (2017), "Social constructivism in social science and science wars", Lippert-Rasmussen, K., Brownlee, K. and Coady D. (Ed.s), *A Companion to Applied Philosophy*. John Wiley & Sons, Ltd., Oxford, pp.455-468.

Dijkstra, T.K. and Henseler J. (2015), "Consistent partial least squares path modeling", *MIS Quarterly*, Vol. 39 No. 2, pp.297-316.

Eberle, T.S. (2019), "Variations of constructivism", Pfadenhauer, M. and Knoblauch, H. (Ed.s), *Social Constructivism as Paradigm? The Legacy of the Social Construction of Reality*. Routledge, London, pp.131-151.

Edwards, D. (2014), *Properties*. Polity Press, Cambridge.

Feynman, R.P. (1974), "Cargo cult science", *Engineering and Science*, Vol. 37 No. 7, pp.10-13.

Gergen, K.J. and Gergen, M.M. (2007), "Social construction and research methodology", Outhwaite, W. and Turner, S.P. (Ed.s), *The Sage Handbook of Social Science Methodology*. Sage Publications, London, pp.461-478.

Goodhue, D., Lewis, W. and Thompson, R. (2007), "Statistical power in analyzing interaction effects: questioning the advantage of pls with product indicators", *Information Systems Research*, Vol. 18 No. 2, pp.211-227.

Hacking, I. (1983), *Representing and Intervening: Introductory Topics in the Philosophy of Natural Science.* Cambridge University Press, Cambridge.

Haenlein, M. and Kaplan, A.M. (2004), "A beginner's guide to partial least squares analysis", *Understanding Statistics*, Vol. 3 No. 4, pp.283-297.

Haig, B.D. (2018), *The Philosophy of Quantitative Methods*. Oxford University Press.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed a silver bullet", *Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp.139-152.

Hair, Jr., J.F., Howard, M.C. and Nitzl, C. (2020), "Assessing measurement model quality in PLS-SEM using confirmatory composite analysis", *Journal of Business Research*, Vol. 109 No. March, pp.101-110.

Hair, J.F., Sarstedt, M. and Ringle, C.M. (2019), "Rethinking some of the rethinking of partial least squares", *European Journal of Marketing*, Vol. 53 No. 4, pp.566-584.

Hawley, J.C., Bampos, N., Abraham, R.J. and Sanders, J.K.M. (1998), "Carboxylate and carboxylic acid recognition by tin(iv) porphyrins", *Chemical Communications*, Issue 6, pp.661-662.

Held, B.S. (1996), “Constructivism in psychotherapy: truth and consequences”, Gross, P.R., Levitt, N. and Lewis, M.W. (Ed.s), *The Flight From Science and Reason. Annals of the New York Academy of Sciences*, Vol. 775, pp.198-206.

Henseler, J. (2017), “Bridging design and behavioral research with variance-based structural equation modeling”, *Journal of Advertising*, Vol. 46 No. 1, pp.178-192.

Henseler, J., Dijkstra, T.K., Sarstedt, M., Ringle, C.M., Diamantopoulos, A., Straub, D.W., Ketchen, Jr., D.J., Hair, J.F., Hult, G.T.M. and Calantone, R.J. (2014), “Common beliefs and reality about PLS: comments on Rönkkö and Evermann (2013)”, *Organizational Research Methods*, Vol. 17 No. 2, pp.182-209.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), “A new criterion for assessing discriminant validity in variance-based structural equation modeling”, *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp.115-135.

Henseler, J., Ringle, C.M. and Sincovics, R.R. (2009), “The use of partial least squares path modeling in international marketing”, *Advances in International Marketing*, Vol. 20, pp.277-319.

Howard, T. (2011), *Coronal Mass Ejections: An Introduction*. Springer, New York.

Howell, R.D., Breivik, E. and Wilcox, J.B. (2007), “Reconsidering formative measurement”, *Psychological Methods*, Vol. 12 No. 2, pp.205-218.

Hunt, S.D. (1990), “Truth in marketing theory and research”, *Journal of Marketing*, Vol. 54 No. 3, pp.1-15.

Hunt, S.D. (1991), *Modern Marketing Theory: Critical Issues in the Philosophy of Marketing Science.* South-Western Publishing Co., Cincinnati, Ohio.

Hunt, S.D. (1992), “For reason and realism in marketing”, *Journal of Marketing*, Vol. 56 No. 2, pp.89-102.

Kim, J. (2010), *Essays in the Metaphysics of Mind.* Oxford University Press, Oxford.

Kukla, A. (2000), *Social Constructivism and the Philosophy of Science.* Routledge, London.

Latour, B. and Woolgar, S. (1986), *Laboratory Life: The Construction of Scientific Facts.* 2nd Edition. Princeton University Press, Princeton, New Jersey.

Linker, M. (2001), “Epistemic relativism and socially responsible realism: why Sokal is not an ally in the science wars”, *Social Epistemology*, Vol. 15 No. 1, pp.59-70.

Lyotard, J-F. (1984), *The Postmodern Condition: A Report on Knowledge*. Manchester University Press.

Mandler, T. (2019), “Beyond reach: an extended model of global brand effects”, *International Marketing Review*, Vol. 36 No. 5, pp.647-674.

Markus, K.A. and Borsboom, D. (2013), *Frontiers of Test Validity Theory: Measurement, Causation, and Meaning*. Routledge, New York.

Massimi, M. (2018), “Perspectivism”, Saatsi, J. (Ed), *The Routledge Handbook of Scientific Realism*. Routledge, London, pp.164-175.

McDonald, R.P. and Mulaik, S.A. (1979), “Determinacy of common factors: a nontechnical review”, *Psychological Bulleting*, Vol. 86 No. 2, pp.297-306.

McIntosh, C.N., Edwards, J.R. and Antonakis, J. (2014), “Reflections on partial least squares path modeling”, *Organizational Research Methods*, Vol. 17 No. 2, pp.210-251.

Merton, R.K. (1973a), “The normative structure of science”, Storer, N.W. (Ed), *The Sociology of Science: Theoretical and Empirical Investigations*. The University of Chicago Press, Chicago, pp.267-278.

Merton, R.K. (1973b), “Paradigm for the sociology of knowledge”, Storer, N.W. (Ed), *The Sociology of Science: Theoretical and Empirical Investigations*. The University of Chicago Press, Chicago, pp.7-40.

Mulaik, S.A. (2009), *Foundations of Factor Analysis*. 2nd Edition. CRC Press, Boca Raton.

Needham, Paul (2018), “Scientific realism and chemistry”, Saatsi, J. (Ed), *The Routledge Handbook of Scientific Realism*. Routledge, London, pp.345-356.

Nelson, H.G. and Stolterman, E. (2012), *The Design Way: Intentional Change in an Unpredictable World*. 2nd Edition. The MIT Press, Cambridge, Massachusetts.

Pennock, R.T. (2019), *An Instinct for Truth: Curiosity and the Moral Character of Science*. The MIT Press, Cambridge, Massachusetts.

Peter, J.P. (1992), “Realism or relativism for marketing theory and research: a comment on Hunt's ‘scientific realism’”, *Journal of Marketing*, Vol. 56 No. 2, pp.72-79.

Putnam, H. (1979), *Mathematics, Matter and Methods: Philosophical Papers, Volume I*. 2nd Edition. Cambridge University Press.

Rigdon, E.E. (2012), “Rethinking partial least squares path modeling: in praise of simple methods”, *Long Range Planning*, Vol. 45 No. 5-6, pp.341-358.

Rigdon, E.E. (2016), “Choosing PLS path modeling as analytical method in European management research: a realist perspective”, *European Management Journal*, Vol. 34 No. 6, pp.598-605.

Rigdon, E.E., Becker, J-M. and Sarstedt, M. (2019), “Factor indeterminacy as metrological uncertainty: implications for advancing psychological measurement”, *Multivariate Behavioral Research*, Vol. 54 No. 3, pp.429-443.

Rönkkö, M. and Evermann, J. (2013), "A critical examination of common beliefs about partial least squares path modeling", *Organizational Research Methods*, Vol. 16 No. 3, pp.425-448.

Rönkkö, M., McIntosh, C.N. and Antonakis, J. (2015), "On the adoption of partial least squares in psychological research: caveat emptor", *Personality and Individual Differences*, Vol. 87, pp.76-84.

Rönkkö, M., McIntosh, C.N., Antonakis, J. and Edwards, J.R. (2016), "Partial least squares path modeling: time for some serious second thoughts", *Journal of Operations Management*, Vol. 47-48 November, pp.9-27.

Rorty, R. (1998), *Truth and Progress: Philosophical Papers, Volume 3.* Cambridge University Press, New York.

Rowbottom, D.P. (2018), "Instrumentalism", Saatsi, J. (Ed), *The Routledge Handbook of Scientific Realism*. Routledge, London, pp.84-95.

Schuberth, F. (2020), "Confirmatory composite analysis using partial least squares: setting the record straight", *Review of Managerial Science*, Vol. 14 https://doi.org/10.1007/s11846-020-00405-0.

Schuberth, F., Henseler, J. and Dijkstra, T.K. (2018), "Confirmatory composite analysis", *Frontiers in Psychology*, Vol. 9, 2541, doi: 10.3389/fpsyg.2018.02541.

Sokal, A. (2008), *Beyond the Hoax: Science, Philosophy and Culture*. Oxford University Press, Oxford.

Tenenhaus, M., Vinzi, V.E., Chatelin, Y-M. and Lauro, C. (2005), “PLS path modeling”, *Computational Statistics & Data Analysis*, Vol. 48 No. 1, pp.159-205.

Weinberg, D. (2014), *Contemporary Social Constructionism.* Temple University Press Philadelphia.

Wilcox, J.B., Howell, R.D. and Breivik, E. (2008), “Questions about formative measurement”, *Journal of Business Research*, Vol. 61 No. 12, pp.1219-1228.

Zackariasson, U. (2018), “Introduction: engaging relativism and post-truth”, Stenmark, M., Fuller, S. and Zackariasson, U. (Ed.s), *Relativism and Post-Truth in Contemporary Society: Possibilities and Challenges*. Palgrave Macmillan, Cham, Switzerland, pp.1-17.

Zinkhan, G.M. and Hirschheim, R. (1992), “Truth in marketing theory and research: an alternative perspective”, *Journal of Marketing*, Vol. 56 No. 2, pp.80-88.

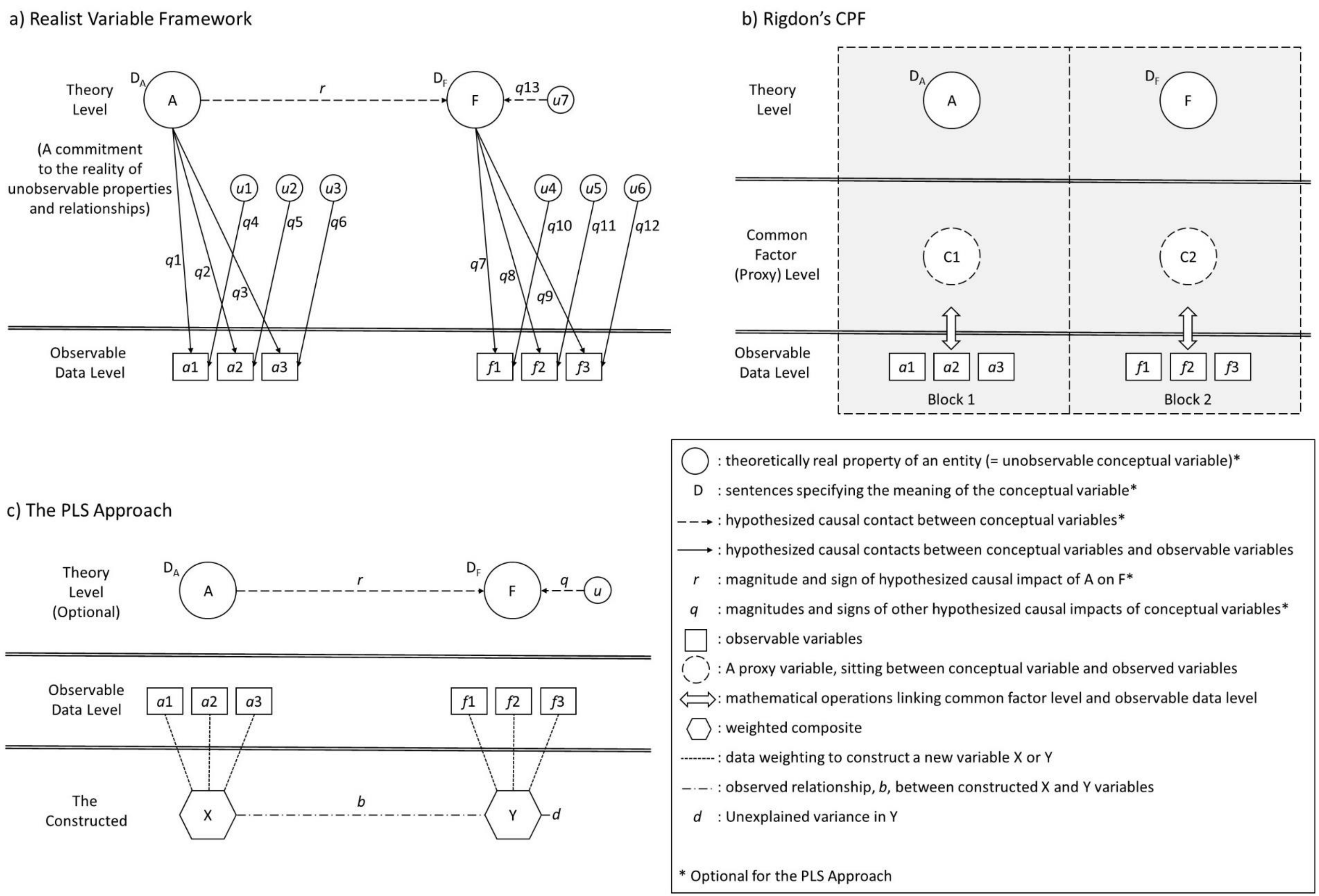

Figure 1: Comparing the Realist Variable Framework with Rigdon's CPF and the PLS Approach

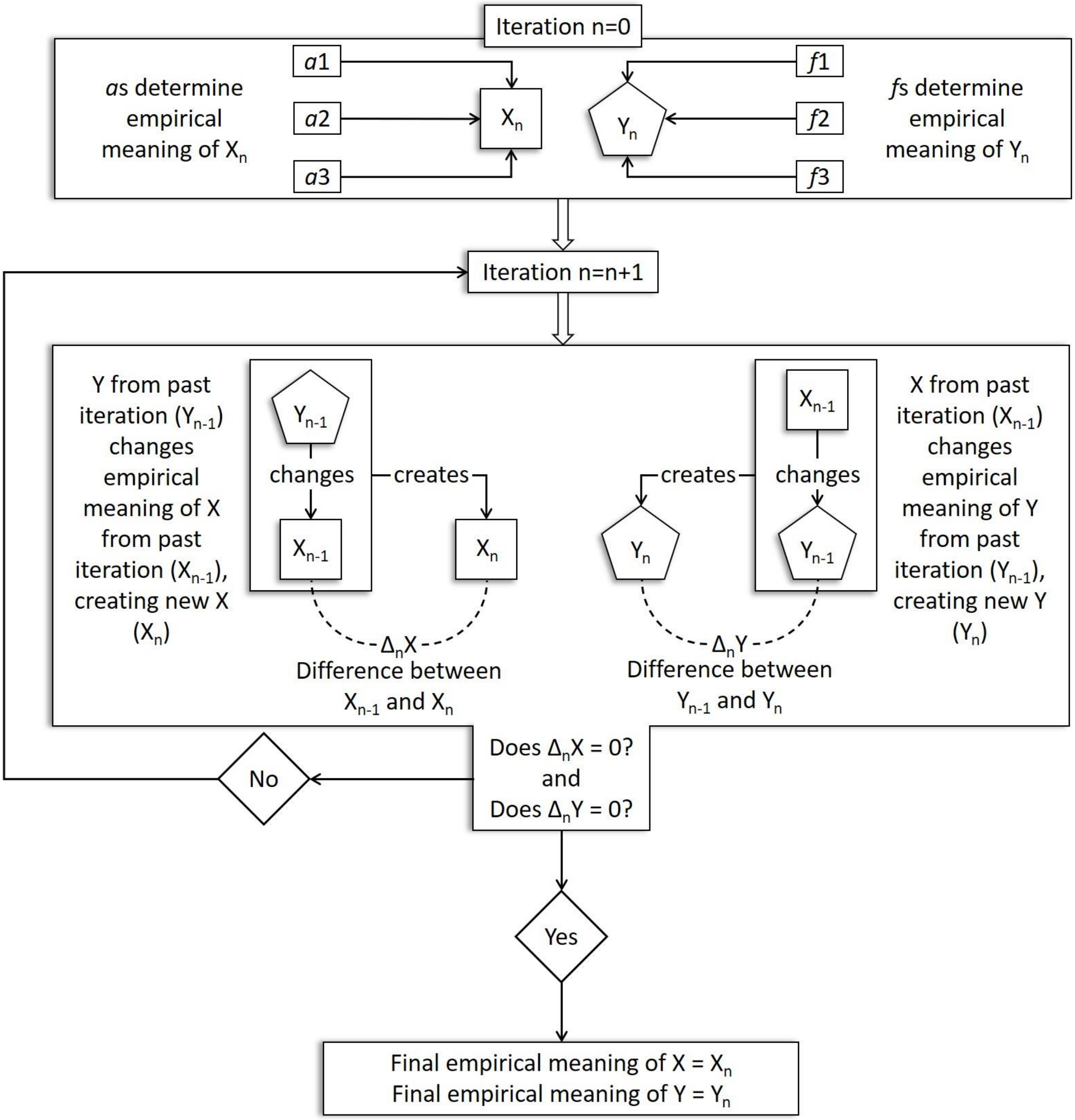

Figure 2: How PLS Gives its Composites Empirical Meanings