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ABSTRACT: We discuss the cyclical nature of action research (AR) in information systems (IS) and contrast it with other research approaches commonly used in IS. Often those who conduct AR investigations build on their professional expertise to provide a valuable service to a client organization while at the same time furthering knowledge in their academic fields. AR is usually conducted using an interpretive research approach, but many doctoral IS students, as well as junior and senior IS researchers, are likely to be expected to conduct research in a predominantly positivist fashion, even as they are determined to conduct an AR study that builds on their professional expertise. We argue that these IS researchers can successfully employ AR in their investigations as long as they are aware of the methodological obstacles that they may face, and have the means to overcome them. The following key obstacles are discussed: low statistical power, common-method bias, and multi-level influences. We also discuss two important advantages of employing AR in

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positivist IS investigations, from a positivist perspective: AR's support for the identification of omitted variables and J-curve relationships. The study's contribution is expected to enhance our knowledge of AR and foster its practice.

KEY WORDS AND PHRASES: action research, common-method bias, J-curve relationships omitted variables, positivist research, statistical power.

Action research (AR) appears to have been independently pioneered in the United States and England in the 1940s. Kurt Lewin, a German-born social psychologist is generally regarded as having pioneered AR in the United States through his field studies, and in England the AR approach was pioneered by the Tavistock Institute of Human Relations [8, 19, 28]. There have been two influential journal special issues of AR in information systems (IS) previously [3, 24] and other good examples are also found [10, 11, 13, 26]. Yet as Avison et al. [2] show, there has been a recent decline in AR in IS that is published in our leading journals and it is therefore appropriate to introduce the particular strengths of AR to a new research audience.

There are many AR variations, but they have in common "action" that takes place in a real organization setting involving researchers and practitioners and "research." In IS, this action might involve developing information systems in an organization or help ensure that the new IS is diffused successfully throughout that organization. The research side is sometimes forgotten and then the so-called research is more akin to consultancy. But AR needs to concern contributions to research through the testing of ideas and theories in practice and/or contribution to theory by way of learning from this practice in such a way that AR is rigorous as well as relevant.

The involvement of researchers, along with practitioners, in the change process is crucial. Researchers are not merely observers of the action, as they might be in case research, for example. They are actually doing the action, normally in collaboration with practitioners. AR is particularly appropriate in messy and complex real-world situations. Bittner and Leimeister [5] describe one such project and show how collaboration in AR leads to an improved situation.

The Cyclical Nature of AR

AR usually involves cyclical interactions where researchers and practitioners participate. Very often an AR project involves a group of researchers working on an IS issue in an organization with several practitioners. According to Susman and Evered [33], action research investigations and related knowledge comprise five stages: diagnosing, action planning, action taking, evaluating, and specifying learning. Usually all but the specifying learning phase concern both researchers and practitioners, and where organizational learning [1] takes place, all phases might include both researchers and practitioners. On the other hand, in organizations where collaboration and participation are less practiced, then practitioner involvement might be much less evident.

The diagnosing stage, where the AR cycle usually begins, is marked by the identification of an improvement opportunity or a general problem to be solved for the practitioner with help from the researcher. In the following stage, action planning, alternative courses of action to attain the improvement or solve the problem are considered. In the action-taking stage we see the implementation of one of the courses of action considered in the previous stage. The evaluating stage involves the practical assessment of the outcomes of the selected course of action. In the final stage, specifying learning, the researcher builds on the outcomes of the evaluating stage to create knowledge about the situation under study that is expected to have a certain degree of external validity (i.e., to generalize to similar contexts).

As illustrated in Figure 1, the possibilities of generalization become more evident where many AR cycles are practiced by the researchers, for example, for different projects at the same organization or a similar project at different organizations. As well as increasing the validity of the observations through further AR experiences, further cycles will increase the research scope insofar as no two projects will be the same.

Susman and Evered's AR cycle provides a conceptual view of the general way in which AR inquiry is conducted. This can be seen as "classic" AR, but many AR projects do not fit neatly into the AR cycle—AR is not a laboratory experiment, it takes place in the real world! Moreover, certain AR schools incorporate unique characteristics that deviate from Susman and Evered's view [3, 12]. Baskerville and Wood-Harper [4] provide a review of different AR approaches. However, because any AR needs to inform research as well as practice, we would discount most consultancy (which concentrates on practice rather than research) and action learning (which is about good learning rather than research), for example, both included in the Baskerville and Wood-Harper review.

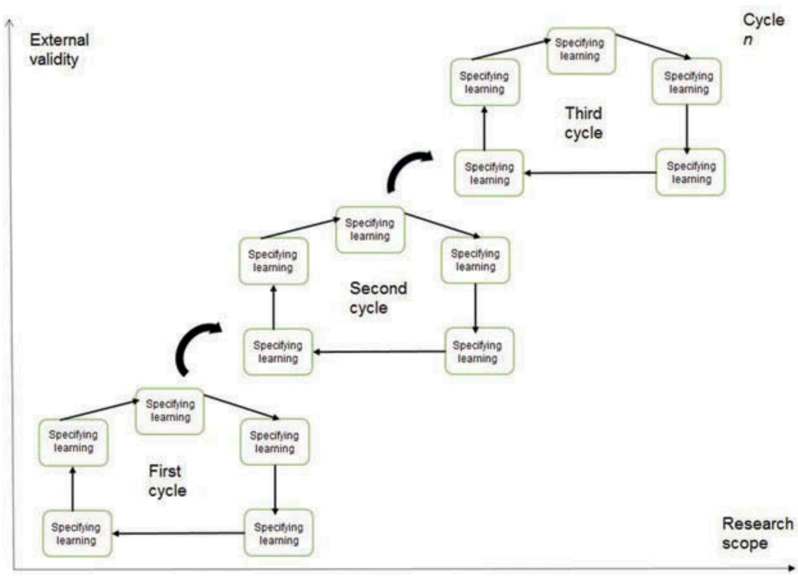

Figure 1. Action Research Cycles Leading to Generalized Knowledge

Contrasting AR with Other Major IS Research Approaches

IS AR typically entails the study of a mainstream IS research topic employing AR as the primary investigative approach. Since in the field of IS a frequent concern is the impact that technologies have on organizations and their individual members, a common form of IS AR investigation involves the study of the impact of the use of an information or communication technology in a practitioner organization. Major research approaches employed in IS that can be contrasted with AR are experimental, survey, and case research. Table 1, adapted from Kock [19], contrasts these approaches.

Of the above research approaches, the most similar to AR is case research. While in both case research and AR the researchers typically study a small sample of practitioner organizations (or a single practitioner organization) in depth, AR's defining characteristic is its dual goal of improving the situation being studied and at the same time generating relevant knowledge. Notably, in AR these two goals are attained *while* the investigation is taking place. For example, if the researcher conducts an in-depth study of the implementation of a new technology aimed at providing real-time business analytics to sales personnel in a large automaker, then perhaps this would be an example of case research. However, if the researcher helps in the development of the business analytics technology, then this would be an example of AR.

Table 1. Contrasting Action Research with Other Major Information Systems Research Approaches

Approach	Description
Experimental research	Rooted in the scientific practice of biologists and physicians (as well as other groups devoted to the "natural" sciences), variables are manipulated over time, associated numeric data are collected, and causal or correlation models are tested through standardized statistical analysis procedures.
Survey research	Rooted in the work of economists and sociologists, the researchers typically have a considerable sample to be analyzed, which suggests the use of questionnaires with close-ended questions that are easy answered and permit quantitative evaluation "a posteriori."
Case research	Rooted in general business studies, particularly those using what is referred to as the "Harvard Method," researchers typically study a small sample of organizations in depth. Cases are analyzed either to build or validate models or theories, typically through collection of textual data in interviews.
Action research	Rooted in studies of social and work-related issues, researchers typically study a small sample of organizations in depth, using participant observation and interviews as key data collection approaches. It is dentified by its dual goal of both improving the situation being studied and at the same time generating relevant knowledge.

AR places the researcher “in the middle of the action.” Therefore, the data collected as part of an AR investigation tend to be very rich. However, AR is perhaps not the most “efficient” approach to scholarly inquiry. One can easily see that IS AR is “messier,” and would likely demand more time and effort from the researcher. But it scores high in terms of practical relevance in the eyes of both academics and industry professionals. The field of IS has long strived for practical relevance, as evidenced by the rigor versus relevance debate in IS [32], and AR addresses both.

By helping a practitioner organization, a researcher conducting an IS AR investigation may play a relevant role in improving the organization and the work of its members. To accomplish that, he or she will normally facilitate change in the organization. Change is not always welcomed by all organizational members. Researchers have to satisfy two “masters” [24]. These are the practitioner organization, with its IS-related needs, and the IS research community, whose main scholarly debate vehicles are selective publication outlets. For example, academic pressure may guide the researcher toward more than one organization, application type, or country to enable generalized findings that would be useful to the research community, whereas organization pressure might suggest total commitment to the one organization. If the researcher is a doctoral student, then such “tugs of war” can be particularly difficult to resolve because of the pressure to ensure the Ph.D. is completed in good time. All this is very challenging, but the satisfaction of helping to directly influence practice along with contributing to our research knowledge make AR particularly rewarding for the researcher, and the knowledge gained can also be particularly relevant for teaching purposes. Most IS AR, including the examples mentioned above, follows an interpretive approach. To encourage such studies, we devote the rest of this article to discussing a positivist approach to AR.

Conducting Positivist Action Research

If a researcher is expected to conduct an IS study in a positivist fashion, how can he or she conduct such a study employing AR? For example, let us consider a scenario where a researcher has had extensive professional experience, including senior management experience, in the U.S. pharmaceutical industry. This industry experience involved facilitating the use of a sophisticated collaborative technology by teams of workers. The technology partially automates and guides the work of teams through the various steps involved in the development of new medical drugs.

In our scenario the researcher is offered the opportunity to conduct an AR study as part of the requirements to earn a Ph.D. degree in IS. She is expected to serve as the facilitator of the collaborative technology use to various teams in three pharmaceutical companies that are the sponsors of a business school in the United States. The school has a strong preference for the use of complex multivariate statistical methods, particularly structural equation modeling (SEM), to test causal models. The school’s decisive bias toward positivist research is obvious. The researcher must meet the methodological requirements stemming from the preference for SEM and the positivist research bias, even as she is determined to conduct an AR study that builds on her professional expertise.

Many doctoral IS students, as well as junior and senior IS researchers, are likely to face scenarios similar to the one outlined above. In numerous institutions around the world, IS investigators are expected to test theories in a positivist fashion. IS researchers can successfully employ AR in their investigations, as long as they are aware of the methodological obstacles that they are likely to face, and of possible ways to overcome them.. We discuss the following obstacles in this paper: low statistical power, common method bias, and multilevel influences. At the end of this paper we also discuss two important advantages of employing AR in positivist IS investigations, from a positivist perspective; namely, AR's support for the identification of omitted variables and J-curve relationships.

Variables and Hypotheses

Structural equation modeling is extensively used in IS research. Two main classes of SEM have found widespread use in the IS field as well as in many other academic fields where behavioral research is conducted: covariance-based and variance-based SEM [22, 23]. Our discussion in this study is aimed at SEM users in general, whether they use covariance-based or variance-based SEM. We focus on the aspects of SEM that would be recognized as relevant by users in both camps. Conceptually speaking, SEM is a very broad technique, encompassing many other methods.

Most statistical methods employed in IS research—such as analysis of variance, multiple regression, and path analysis—can be conceptually seen as special cases of SEM [18, 22, 23, 27]. Common characteristics of positivist studies employing SEM are the presence of well-defined constructs, which are represented by latent variables, and hypotheses that specify causal links among constructs. The hypotheses are developed based on existing theory and past empirical research, with SEM data collection and analyses being aimed at testing the hypotheses. The ultimate goal is to incrementally test and refine theoretical ideas that can be expressed through causal relationships.

Latent variables are used in SEM to measure constructs that cannot be directly quantified, which are abundantly found in IS research and in behavioral research in general. For example, one's job satisfaction cannot be directly quantified in a practical manner. One might argue that direct measurement could be implemented through periodic collection of blood samples from employees and testing of concentrations of pleasure hormones (e.g., dopamine), but this is not practical. Instead, researchers propose statements of the type "I am happy with my job" and "My job gives me enjoyment" in questionnaires answered on Likert-type scales (e.g., 1 = strongly disagree to 7 = strongly agree). Multiple redundant statements are then used to minimize, via SEM techniques, the errors inherent in using questionnaires to measure constructs.

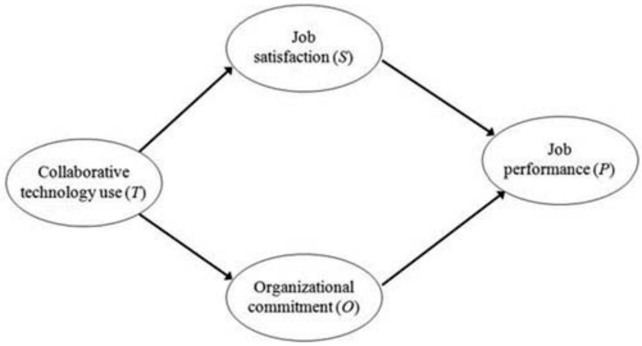

Figure 2. Illustrative Model

Let us assume that, in our scenario, the three pharmaceutical companies are interested in increasing not only job performance but also job satisfaction and organizational commitment because of the high employee turnover in their industry. That is, the companies would not want to increase the job performance of employees only to see those employees leave. Therefore, the causal model tested through the AR project would include the following variables (see Figure 2): collaborative technology use (T), job satisfaction (S), organizational commitment (O), and job performance (P). The researcher's main service to each organization would be to facilitate the use of the technology through a collaborative work technique that is composed of multiple steps and is especially tailored to the technology.

The members of the senior management teams in the companies believed that the facilitated use of the collaborative technology would significantly simplify teamwork and allow for greater knowledge exchange, and thus significantly improve employee morale and performance. The hypotheses that would make up the model, in the context of new medical drug development by teams, would be: the greater collaborative technology use is, the greater is job satisfaction ($T \rightarrow S$); the greater collaborative technology use is, the greater is organizational commitment ($T \rightarrow O$); the greater job satisfaction is, the greater is job performance ($S \rightarrow P$), and the greater organizational commitment is, the greater is job performance ($O \rightarrow P$).

Low Statistical Power

In our scenario, the researcher has to provide a service to the drug development teams in the client organizations, which requires a significant time commitment. This is a common occurrence in AR investigations in general, and thus tends to limit the size of the sample of data to be analyzed. Even if the unit of analysis is the individual in a team, which we will assume to be the case in our illustrative scenario (this leads to multilevel influences, discussed below), the sample size may be small enough to compromise statistical power. A study's statistical power is the probability that it will avoid false negatives, or type II errors—mistakenly rejecting hypotheses that refer to real (or true) effects, and that thus should not be rejected.

A general rule of thumb that arguably applies to SEM in general, including covariance-based (employing software tools like LISREL; e.g., [7]) and variance-based forms (employing tools like WarpPLS; e.g., [14]), is that the sample size should satisfy Equation (1), where: $\hat{N}$ is the sample size estimate; $z_{.95}$ and $z_{.8}$ are the z-scores associated with the values .95 and .80, which assume the use of 95 percent confidence levels (or P-values significant at the .05 level) for hypothesis testing and statistical power of 80 percent; and $|\beta|_{min}$ is the minimum significant absolute path coefficient expected or observed in the model [23]:

$$\hat{N} > \left(\frac{z_{.95} + z_{.8}}{|\beta|_{min}} \right)^2 . \tag{1}$$

We can use the Excel function NORMSINV(x) to obtain the values for $z_{.95}$ and $z_{.80}$, NORMSINV(.95) and NORMSINV(.80), which are 1.645 and 0.842, respectively. Therefore, the sample size should satisfy: $\hat{N} > \left(2.486/|\beta|_{min}\right)^2$. For example, if the minimum significant absolute path coefficient observed in the model is .2 for the path $T \rightarrow S$ than a minimum sample size of approximately 155 is needed to achieve a statistical power of 80 percent; calculated as the nearest integer greater than: $(2.486/.2)^2 = 154.505$.

As we can see above, the strength of the weakest significant path coefficient in an SEM model is what drives the minimum sample size needed to achieve a statistical power of 80 percent. Researchers conducting positivist IS AR can use the equation above to ensure that they have the minimum sample size required to test each of their hypotheses. Those researchers are generally advised to focus their positivist IS AR studies on hypotheses that are likely to be associated with strong effects, leaving the test of weak effects to studies employing other research approaches (e.g., large surveys). For example, if all path coefficients in a model are expected to have absolute values of .3 or higher, then a sample size of 69 would be acceptable since: $(2.486/.3)^2 = 68.669$.

Common Method Bias

Common-method bias occurs when artificially induced common variation is introduced into the variables in a model, due to the data collection method employed [29]. This common variation may be introduced in the entire sample or in specific subsamples. For example, let us assume that the AR interventions in which the researcher in our scenario is involved are top-down, with participation directives going from senior management to the employees of the three pharmaceutical companies. The senior management teams of the companies clearly communicate their interest in improving employee well-being. Nevertheless, the top-down nature of the interventions makes employees want to show strong commitment to the project and their organizations, whether they are really committed to them or not. This makes all the employees who provide data to the study exaggerate, in a positive way, their answers to question-statements associated with the latent variables in the model: collaborative technology use (T), job satisfaction (S), organizational commitment (O), and job performance (P).

In this example the shared variation may lead to multicollinearity, which can be measured through model-wide variance inflation factors associated with each of the latent variables [25, 31]. The end result is an artificial increase in the correlations among the latent variables, which would tend to lead to an overestimation of all the path coefficients in the model [20]. This overestimation of path coefficients increases the likelihood of false positives, or type I errors, where hypotheses that should be rejected are mistakenly accepted. Generally, the probability that a false positive will occur in SEM is expected to be quite low, at no more than 5 percent.

The risk of common-method bias in positivist IS AR is high if researchers are not very careful with the way they present their interventions to their AR subjects. AR investigators should present their research studies in a strictly neutral way, and ensure that management does the same. Participation should be presented as voluntary. In our scenario, this would mean that the researcher and management in the three pharmaceutical companies would have to present the AR interventions as "experimental," indicating the possibility that some or even many of the teams where facilitated collaborative technology use occurred could fail. That is, team members whose work was facilitated through the AR project might display lower job morale and performance than they would have without any facilitation. In other words, AR interventions should be presented in part as field experiments with somewhat uncertain outcomes. Accordingly, employees should be allowed to decide whether they will participate and to what degree they will participate.

Multilevel Influences

Given the collaborative nature of work in organizations in general, it is common in AR projects for researchers to facilitate the work of teams. This poses a dilemma: should the data be collected at the team or individual level? For example, let us assume that in our scenario the researcher facilitated 5 teams in each of the three pharmaceutical companies, each team with 10 individuals. If the unit of analysis in the AR study is the team, then the sample size would be 15, which is very low. On the other hand, if the unit of analysis is the individual team member, then the sample size is a much larger 150. However, team membership may influence the various links in the model, and thus the results [17].

Here the researcher needs to employ multilevel analysis techniques [16]. This essentially means that the researcher must add variables that reflect the influences of team performance on the endogenous latent variables in the model [14, 23], so that she can control for those influences (see Figure 3). For example, a new variable, which could be referred to as team collaborative technology use (T_t), and which

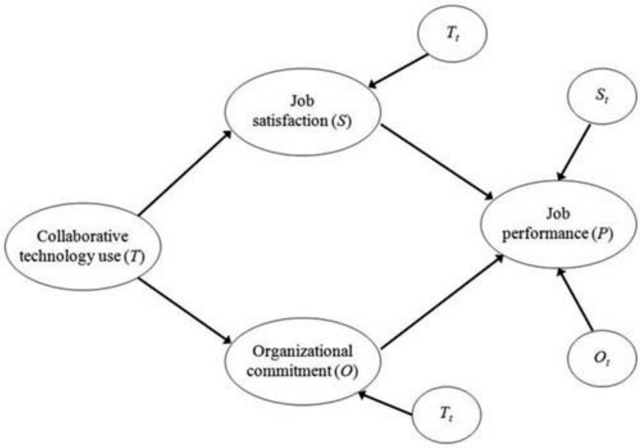

Figure 3. Controlling for Multilevel Influences

would store the average amount of collaborative technology use for each team, could be added to the model pointing at the latent variables to which collaborative technology use (T) points. The same could be done for job satisfaction, with a variable S_t pointing at the latent variable pointed at by S; and for organizational commitment, with O_t pointing at the latent variable pointed at by O.

This approach would allow the researcher to use the individual as the unit of analysis in the model, and thus the larger sample size of 150, while at the same time controlling for the influence of team factors on the individuals. The new variables would have the effect of removing the biases in the path coefficients for competing links. For example, the link $T_t \rightarrow S$ would correct the path coefficient for $T \rightarrow S$, by allowing the latter link to be estimated controlling for the team membership influence.

Omitted Variables

The close involvement of the researcher with the research subjects in positivist IS AR can be seen as limiting in some respects. As noted above, it increases the likelihood of common-method bias if certain precautions are not taken. On the other hand, this close involvement has some advantages that arguably are not present in other research approaches normally employed for positivist inquiry. One such advantage is the ability to identify omitted variables [9], or variables that were not included in the model during the hypothesis development stage that usually precedes positivist investigations.

For example, the researcher in our scenario may have observed that those individuals who tended to display prosocial behavior, or behavior that tends to benefit others in their organizations, tended to also display high levels of collaborative technology use (T), job satisfaction (S), organizational commitment (O), and job

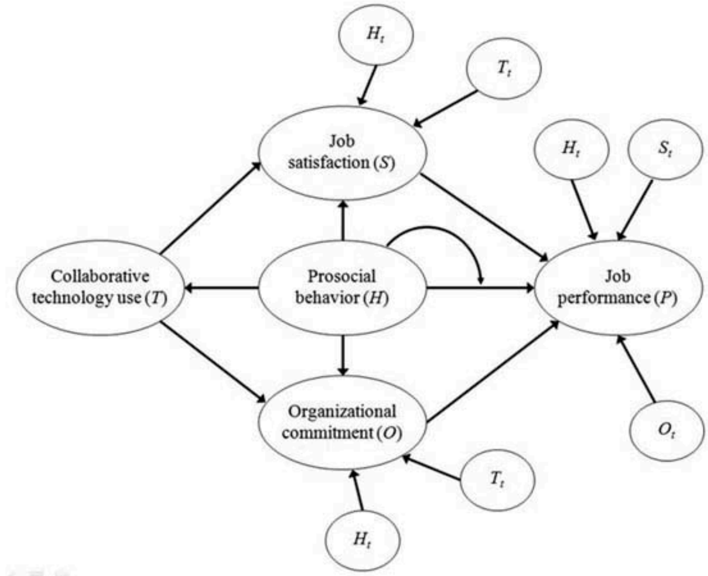

Figure 4. Omitted Variable and J-Curve Relationship

performance (P). Being closely involved with the individuals participating in the AR projects in the three pharmaceutical companies, the researcher is then able to define multiple redundant questions that she uses to collect additional data and measure a new latent variable: prosocial behavior (H).

This new latent variable is then included in the model (see Figure 4). As previously done to control for multilevel (or team) influences (e.g., with T_t), another new variable (H_t) would have to be added to the model, with various links. Note that without the inclusion of this new variable H, and corresponding team-related variable H_t, all the path coefficient estimates would be distorted in ways that could lead to misleading theoretical conclusions. This type of omission would normally cause the path coefficients to be overestimated with respect to their true values. Nevertheless, some of the path coefficients may be underestimated, or even change signs with respect to the true values. This latter sign reversal phenomenon is referred to as Simpson's paradox, and recent research suggests that it is a relatively common yet widely ignored phenomenon in IS investigations [21].

J-Curve Relationships

Another advantage of the close involvement of the researcher with the research subjects in positivist IS AR is the possible identification of J-curve relationships, which, as the name implies, are causal associations between pairs of variables in a model that lead to J-curve shapes [6, 21, 30]. The shape may be inverted, resulting in an upside-down J-curve shape. The term "U-curve" is also used to refer to these relationships. They are particularly important because they are a common occurrence, arising from "self-moderation" (illustrated below), and because in them the path coefficient for the predictor-criterion variable link varies to the point of changing sign for different values of the predictor variable.

For instance, let us assume that the researcher in our scenario also identified the following behavioral pattern in the three pharmaceutical companies. For new employees, increases in prosocial behavior (H) seemed to lead to lower job performance (P), as those individuals' prosocial behavior requires altruistic time commitment that is not immediately reciprocated because of the new employees' relative low social status in their organizations. As they spend more time with their companies, a proportion of those individuals engaged in prosocial behavior acquire greater social status, which leads to more instances of reciprocation. Moreover, as they gain more social status, individuals engaged in prosocial behavior are regularly informed by their supervisors and peers, via spontaneous praise and positive annual evaluations, that such behavior positively affects their job performance (P). This leads those individuals to engage in even more prosocial behavior (H), which is perceived as more valuable by others because of the prosocial individuals' increased social status, further increasing the strength of the $H \rightarrow P$ link. This can be modeled as H moderating its own link with P, giving rise to a quadratic relationship, where P is a function of H^2 (curved link in the figure).

The identification of this type of self-moderation allows researchers to properly model J-curve relationships, and thus more accurately estimate the corresponding path coefficients. If J-curve relationships are force-modeled as linear, their path coefficients would tend to be underestimated (see, e.g., [15, 21]). This underestimation is particularly problematic in positivist IS AR, given the propensity of this type of research to present low statistical power. As noted above, the power of an SEM analysis tends to go down with small path coefficients. Conversely, the power increases with large path coefficients. Given these methodological phenomena, it would be reasonable to argue that researchers engaged in positivist IS AR should actively seek to identify J-curve relationships. Other types of nonlinear relationships could be identified as well, but the corresponding discussion is beyond the scope of this study.

Conclusion

Researchers conducting positivist IS AR are likely to face the following methodological obstacles: low statistical power, common-method bias, and multilevel influences. They should be aware of the nature of these obstacles, and of possible ways to overcome them. One could argue that these obstacles should be ignored by researchers who do not subscribe to quantitative positivist research approaches such as SEM. We do not necessary disagree, but remind readers that our discussion above is presented from a positivist perspective. In our illustrative scenario, the researcher's choice of research method and epistemological orientation is constrained.

On the other hand, as we note in our discussion above, there are methodological advantages of employing AR in positivist IS investigations, from a positivist research perspective, that are unlikely to be found in other research approaches usually employed in positivist research. At the source of this is the fact that these latter positivist research approaches tend to intentionally keep the researcher "away" for the research subjects, for example, survey research. Important advantages of positivist IS AR are its support for the identification of omitted variables, and its support for the identification of J-curve relationships.

We hope that our position is clear: we do not believe that IS AR should always be conducted in a positivist fashion, but we *do* believe that IS AR can be done in ways that would be seen as acceptable by positivist researchers.

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