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RESEARCH ARTICLE

MAKING RIGOROUS RESEARCH RELEVANT: INNOVATING STATISTICAL ACTION RESEARCH

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Appendix A

Search of the IS Literature for Statistical AR

Using Academic Search Complete, we sought out any published action research articles taking positivist and/or statistical approaches in the information systems discipline. We searched articles in the Senior Scholars Basket of 8 (*MIS Quarterly*, *Information Systems Research*, *Journal of the Association for Information Systems*, *Journal of Management Information Systems*, *Journal of Information Technology*, *Journal of Strategic Information Systems*, *Information Systems Journal*, *European Journal of Information Systems*) and three additional prominent journals (*Information & Organization*, *Information & Management*, and *Decision Support Systems*). In these journals, for published articles mentioning "action research" in the title, abstract, or keywords, we specified a search for those articles that included *any* of the following words or word stems: "sample size," "statistical* significan*," "positivis*," "null hypothesis," "regression," "ANOVA," "MANCOVA," "structural equation model*," "SEM." Of the 24 articles that the search produced, an examination of each one revealed that the given article may have mentioned one of more of the selected words or word stems (such as "positivis*"), but could not be considered to be positivist (whether quantitative or qualitative) and did not conduct any statistical hypothesis testing.

The search string used was:

> (AB "action research" OR TI "action research") AND TX ("sample size" OR "statistical* significan*" OR positivis* OR "null hypothesis" OR "regression" OR "ANOVA" OR "MANCOVA" OR "structural equation model*" OR SEM) AND SO ("MIS Quarterly" OR "Information Systems Research" OR "Journal of the Association for Information Systems" OR "Journal of Management Information Systems" OR "Journal of Information Technology" OR "Journal of Strategic Information Systems" OR "Information Systems Journal" OR "European Journal of Information Systems" OR "Information & Organization" OR "Information & Management" OR "Decision Support Systems")

Appendix B

Rubric for Theory Selection

Table B1. Rubric for Theory Selection

Step	Description
Gather qualitative and/or quantitative data for diagnostic purposes	As part of the normal process of conducting statistical action research, the researcher should enter the field to collect qualitative and/or quantitative data to both subjectively (as provided by the organization and its employees) and objectively (as framed by the researcher using existing theory) describe the problem at hand.
Identify patterns in the data	As the data are collected, the researcher should identify patterns that emerge. As this pattern identification process unfolds, more data can be collected if needed.
Leverage the patterns to identify any applicable existing theories	The patterns in the data should be used to identify candidate theories. This can be done by aligning the variables and relationships among them that emerge as patterns from the data.
Validate theory selection in the field	Candidate theory/ies should be shared with the client organization in order to assess their validity. If the client organization agrees that the theory/ies fit, then move forward. If the client organization questions the fit, then the researcher should go back to the literature to seek out additional theories – essentially repeating this step until the client organization agrees. An option is to simply formulate a new theory, in case no existing theory is a good fit for the situation. Include multiple organizational constituents, explain theory in lay terms and ask participants to describe organizational events using their understanding of the theory. In this way, the researcher can make sure that the organizational constituents understand the theory. Finally, ask the participants if the theory helps to explain the problem. Multiple theories can be validated for use in diagnosis and intervention stages of statistical AR.
Develop intervention based on theory	Once the candidate theories are validated in the organization, the researcher can then develop the appropriate theory-based intervention.
Validate theory selection based on intervention	Once the intervention has been performed, the researcher should gather additional data in order to further evaluate the appropriateness of the theories that guided the diagnosis and intervention for this particular setting. An intervention's being successful is consistent with the selection of appropriate theories.

Table B2. Applying the Rubric for Theory Selection for this Specific Statistical AR Study	
Step	**Description**
Gather qualitative and/or quantitative data for diagnostic purposes	Data collection started with collecting qualitative data through interviews with individuals that had a wide variety of job descriptions. Quantitative data was collected that showed the number of submissions and the lengths of the validation of submitted knowledge via KMS.
Identify patterns in the data	The following patterns emerged from the interviews: (1) the coach was the most important driver of agents' behavior; and (2) there was much confusion regarding how, where, and by whom the newly submitted knowledge was validated; (3) the knowledge validation process was very long (around 30 days) and quite restrictive.
Leverage the patterns to identify any applicable existing theories	Two theories were identified that provided a good match for the patterns identified above: (1) attribution theory and (2) knowledge validation theory.
Validate theory selection in the field	These two theories were introduced to the project manager (PM) and the team that lead the intervention regarding KMS usage. The researcher who was part of the KMS project team explained the theories to the team and asked the team to provide feedback to support the theories. The KMS project team unanimously agreed that these two theories provided a good explanation for currently observed behaviors regarding limited knowledge submission to the KMS and knowledge reuse. In addition, the researcher collected quantitative data (using survey methodology) to find further support for attribution theory that showed the significant role of the coach in the decision to submit knowledge to the KMS.
Develop intervention based on theory	The KMS project team asked the researcher for suggestions regarding intervention that would persuade the agents to submit knowledge to the KMS and to reuse knowledge that was already in the KMS. The researcher offered a persuasion-based strategy and provided a sample intervention based on this theory. The KMS project team reviewed the suggestion and made changes to some parts of the suggested intervention. This updated intervention was then used to communicate the goal of knowledge submission, knowledge validation, and knowledge reuse from the KMS.
Validate theory selection based on intervention	Three months after the intervention the researcher collected quantitative data using the same survey as during evaluation stage. The results of the data analysis showed the role of the coach was no longer significant in agent's decision to submit knowledge to the KMS but rather it was the knowledge validation process itself that predicted behavior. In addition, the number of new knowledge submissions doubled. The KMS project team voted unanimously that the intervention was a success and suggested to the leadership of DBL Software Company to utilize the same intervention for the rest of the agents as was used in the pilot group. With management deeming the intervention successful, the KMS project team was dismissed.

Table B3. Summary of Theories Used in Diagnosis and Intervention Stages for this Particular Statistical AR	
Variables in Knowledge Validation Theory	**Referents**
Restrictiveness	The review process had a very low acceptance rate
Transparency	No transparency: users believed reviews were done by artificial intelligence or were sent out of the state
Duration	The majority of submissions exceeded 30 days to appear in KMS
Knowledge Submission Frequency	For one group, it was 48 submissions per month, which was considered very low
Knowledge Quality	Deemed not relevant (see page 249)
Variables in Attribution Theory	**Referents**
Internal Causes	Deemed not relevant (see page 251)
External Causes	Knowledge validation process characteristics were the target: *Restrictiveness*: review process had a very low acceptance rate *Transparency*: it was not clear what happened once the new knowledge was submitted *Duration*: the length of the review process exceeded 30 days, which is not acceptable in a highly volatile environment such as help-desk support
Behavior	Knowledge submission frequency
Variables in Persuasion Theory	**Referents**
Source Characteristics	Phased communication
Message Characteristics	Purpose, benefits, and roles Taking agents off the phone is a message in itself.
Audience Characteristics	Deemed not relevant (see page 254)

Appendix C

Description of Interviews

Each interview lasted approximately 30 minutes. These interviews were done during the evaluation stage of the Statistical AR.

Table C1. Description of Interviews

Role	Content of Interview	Number of Interviews
Coach	Discussed their role as coach; nature of their supervision activities of the agents a coach was supervising, agent training, use of IT tools and the KMS, evaluation of agents.	10 unique coaches
Agent (Level I)	Directly observed how agent interacts with client; how agent uses ticket tracking system and KMS.	3 unique agents
Agent (Level I)	Directly observed how agent interacts with client; how agent uses ticket tracking system and KMS; discussed sharing and retrieval of knowledge from KMS.	5 unique agents
Analyst	Discussed their role as learning & assistant manager; responsibilities for the search engine within the KMS; view why there is resistance to adopt the KMS; knowledge validation.	2 unique analysts
SME (subject matter expert)	Discussed their responsibilities, work with agents, usage of KMS (knowledge sharing and retrieval).	10 unique SMEs
KMS technical expert	Discussed the technical specifications of the KMS and his perspective why agents resent using the current KMS.	3 unique experts
Manager for Level III and Level IV escalation team	Discussed role of the team with respect to Level I agents, typical work day of manager, typical day of team he was managing, role of Level I, Level II, Level III, and Level IV agents with respect to KMS, likes and dislikes of KMS.	2 unique managers
Supervisor	Discussed role and value of KMS for business unit (approximately 80 people); discussed pain points of using KMS, role of coaches, ownership of KMS within company.	2 unique supervisors
KMS owner	Discussed structure of KMS, knowledge validation within KMS, use of KMS by agents (both knowledge sharing and knowledge retrieval), integration of KMS with ticketing system.	1 unique KMS owner
Manager for Level I team	Discussed role as team manager, value that comes from KMS for the agents, role of coaches and SMEs and how they help agents, motivation of agents and coaches, issues with KMS.	3 unique managers
Knowledge champion	Discussed knowledge sharing via KMS, knowledge retrieval via KMS, KMS agent training for knowledge sharing and retrieval, success measures for KMS, ownership of knowledge in KMS, pain points regarding KMS usage.	2 unique knowledge champions
Conductor	Discussed job responsibility of a help-desk queue conductor, interaction with agents, interaction with KMS and ticketing system.	2 unique conductors
Technical support manager	Discussed role as technical support manager; interaction with managers, coaches, SMEs, and agents; role of KMS for knowledge sharing and retrieval by agents.	1 unique manager

Appendix D

Survey Development and Data Analysis

The survey was developed following DeVellis's (2003) guidelines. Measures for usefulness and ease of use were adapted from Davis (1989). Professional respect was adapted from Liden and Maslyn (1998). The remaining items for submission frequency, restrictiveness, transparency, and duration of validation were adapted from Durcikova and Gray (2009). All items except items 3 and 4 under professional respect (i.e., PR3 and PR4) were measured on a 7-point Likert scale where 1 = strongly disagree and 7 = strongly agree. PR3 and PR4 were measured using a percent scale, 0% to 100% in 10% increments.

The instrument was first reviewed by colleagues, after which minor edits were made. We pre-tested the survey with three agents at the research site to insure readability and appropriateness of terminology. The final set of items is shown in Table B1.

Table D1. Constructs and Items

Construct	Item
Rejection Rate [PR]	[PR1] It is difficult to get submissions approved.
	[PR2] Getting a submission approved and accepted is easy.
	[PR3] In your experience, what proportion of submissions that you submit to the <system> end up being rejected? (NOTE: response was a percentage)
	[PR4] Based on the experiences your colleagues have shared with you, what proportion of all articles that are submitted to the <system> end up being rejected? (NOTE: response was a percentage)
Transparency [TRANS]	[TRANS1] I am kept informed about the status of my articles to <system>.
	[TRANS2] It is easy for me to see the status of my articles to <system>.
	[TRANS3] I can check at any point in time the status of my articles to <system>.
	[TRANS4] Overall, the article review process is clear.
Duration [TVAL]	[TVAL1] The review process for articles to <system> occurs in a timely manner.
	[TVAL2] The review process for articles to <system> takes far too long.
	[TVAL3] I am satisfied with the amount of time it typically takes for articles to be reviewed and processed.
Respect for Supervisor [RESP]	[RESP1] I am impressed with my <supervisor's> knowledge of his/her job.
	[RESP2] I respect my <supervisor's> knowledge of and competence on the job.
	[RESP3] I admire my <supervisor's> professional skills.
Ease of Use [EOU]	[EOU1] <System> has been easy for me to learn.
	[EOU2] I find it easy to get <system> to do what I want it to do.
	[EOU3] It was easy for me to become skillful at using <system>.
	[EOU4] Overall, I find <system> easy to use.
Usefulness [PU]	[PU1] Using <system> in my job enables me to solve problems more quickly.
	[PU2] Using <system> improves my job performance.
	[PU3] Using <system> in my job increases my productivity.
	[PU4] Using <system> enhances my effectiveness on the job.
	[PU5] Using <system> makes it easier to do my job.
	[PU6] I find <system> to be useful in my job.
Submission Frequency [FRQ]	[FRQ1] I frequently submit articles to <system>.
	[FRQ2] I often contribute articles to <system>.
	[FRQ3] I am a regular contributor to <system>.
	[FRQ4] I submit articles to <system>.

Note: All items measured on a 7-point Likert scale where 1 = strongly disagree and 7 = strongly disagree, unless otherwise indicated.

We sampled the 80 employees involved in the pilot testing of the intervention. We received 56 usable responses in pre-intervention and 64 in post-intervention, resulting in response rates of 70% and 80% respectively. The data were analyzed using SmartPLS 3 (Ringle et al. 2015). PLS is a structural equation modeling technique that allows us to simultaneously evaluate the data and the theory. It is particularly well-suited for our purposes as it is good for the analysis of small data sets (Chin 1998) and is more suited for predictive applications and theory building than covariance-based structural equation modeling (Gefen et al. 2000). We employed bootstrapping (500 samples) to test the significance of the path coefficients in the model.

Following Podsakoff and Dalton (1987), common method bias was tested via factor analysis. The procedure extracted 7 factors explaining 90% of the variance in the underlying data. No single factor had significant loadings for all items. We also utilized the marker-variable technique (Lindell and Whitney 2001), which offers two alternative approaches for assessing common method bias. First, a marker variable that is theoretically unrelated to at least one variable in the study can be identified and incorporated into the instrument. The correlation between the marker variable and the dependent variable is a reliable estimate of common method bias. Second, the second-smallest positive correlation among the manifest variables provides a conservative estimate for common method bias. Given our study design, we employed the second method. After adjustment for the second smallest positive correlation, all significant correlations remained significant. Thus, common method bias was not deemed a problem for our analysis.

We then conducted confirmatory factor analysis to identify items that loaded poorly on their respective constructs. As a result, we dropped three items: items one and four for perceived rejection rate and item one from transparency. We examined the reliability of the remaining measures using three techniques in PLS. We first examined the item loadings to be sure that they were all above .7. Except for one item (the second item in perceived rejection rate at time 2), the loadings met this criteria. Due to the fact that the remaining reliability analysis demonstrates good reliability (ICR = .75), we retained the items. Second, we examined the internal consistency by evaluating the composite reliability. For all items at both time periods, the values exceeded Nunnally's (1978) suggested cutoff of .7. Finally, we calculated the Average Variance Extracted (AVE) for all items. The lowest value was .60, which exceeds Chin's (1998) recommended cutoff of .50. Following Ringle et al (2012), this provides ample evidence of the reliability of the constructs.

Discriminant validity was assessed using two techniques. First, an examination of the correlation of items with their respective constructs revealed that the items correlated most strongly with their intended constructs. Second, the square root of the AVE exceeded all interconstruct correlations. Together, these measures demonstrate that the items discriminated adequately across constructs. To assess potential multi-collinearity, we calculated the variance inflation factors (VIF). VIF values for all variables for both pre-intervention and post-intervention ranged from 1.0 to 1.97, below the suggested threshold value of 3.3 (Kock and Lynn 2012). This provides evidence that multicollinearity was not a potential confound.

Tables D2, D3, and D4 provide the detailed analysis for the reliability and validity of constructs. Tables D4 and D5 shows the item-total correlations for pre-intervention and post-intervention.

Note: Our literature review resulted in three categories that can influence knowledge submission, namely, operating procedures, the organizational environment, and the KMS itself. We discuss the role of the first two in Stage One of Statistical AR. Here, we discuss the role of the third category given that it is a part of the nomological network and this is how we presented the results to DBL Software Company.

As for the third category, there is an extensive literature on technology acceptance (e.g., Davis 1989; Davis et al. 1989; Venkatesh et al. 2003) that addresses, among other things, an individual's perceived usefulness, perceived ease of use, and resultant usage of a system. We note that, based on our interviews, there were no technical problems with the KMS as installed and implemented, including its knowledge submission component. We also observed nothing indicating that DBL Software Company agents blamed features of the KMS for their not making knowledge submissions. However, as part of our diagnosis, we measure certain technology-acceptance relationships, in order to control for any impact they have on making knowledge submissions. We measure perceived ease of use and perceived usefulness using instruments already available from technology acceptance research (e.g., Davis 1989; Davis et al. 1989; Venkatesh et al. 2003) and include them in our hypothesis testing as control variables.

Table D2. Descriptive Statistics, Correlations, and Square Root of AVE: Pre-Intervention											
	# of items	Mean	St. Dev	ICR	PR1	TRANS1	DUR1	RESP1	EOU1	PU1	FRQ1
Perceived Restrictiveness	2	3.62	2.24	0.782	**0.802**						
Process Transparency	2	2.86	2.06	0.958	-0.334	**0.958**					
Duration of Validation	3	4.38	1.87	0.910	-0.464	0.355	**0.880**				
Respect for Coach	3	6.08	1.24	0.950	-0.317	0.239	0.259	**0.929**			
Ease of Use	4	5.00	1.67	0.964	-0.225	0.279	0.457	0.022	**0.934**		
Perceived Usefulness	6	5.43	1.57	0.986	-0.364	0.231	0.532	0.249	0.702	**0.961**	
Submission Frequency	4	3.64	2.04	0.959	-0.360	0.277	0.415	0.416	0.299	0.406	**0.925**

Table D3. Descriptive Statistics, Correlations, and Square Root of AVE: Post-Intervention											
	# of items	Mean	St. Dev	ICR	PR2	TRANS2	DUR2	RESP2	EOU2	PU2	FRQ2
Perceived Restrictiveness	2	4.79	2.94	0.749	**0.779**						
Process Transparency	2	3.73	1.98	0.918	-0.056	**0.889**					
Duration of Validation	3	4.22	1.72	0.971	-0.450	0.404	**0.972**				
Respect for Coach	3	6.37	0.98	0.952	-0.239	0.024	0.168	**0.932**			
Ease of Use	4	5.07	1.36	0.943	-0.201	0.211	0.134	0.073	**0.898**		
Perceived Usefulness	6	5.84	1.39	0.981	0.060	0.229	-0.080	0.026	0.441	**0.946**	
Submission Frequency	4	4.36	1.75	0.952	-0.300	-0.192	0.244	-0.110	0.014	0.116	**0.912**

Table D4: Item-Construct Correlations: Pre-Intervention							
	PR1	**TRANS1**	**TVAL1**	**RESP1**	**EOU1**	**PU1**	**FRQ1**
PR2	**0.79**	-0.24	-0.35	-0.57	-0.21	-0.35	-0.36
PR3	**0.92**	-0.30	-0.45	0.05	-0.16	-0.26	-0.26
TRANS2	-0.34	**0.97**	0.35	0.30	0.42	0.30	0.23
TRANS3	-0.31	**0.97**	0.25	0.17	0.16	0.16	0.29
TVAL1	-0.46	0.30	**0.94**	0.31	0.45	0.53	0.48
TVAL2	-0.37	0.09	**0.85**	-0.10	0.20	0.28	0.14
TVAL3	-0.47	0.41	**0.89**	0.28	0.48	0.54	0.36
RESP1	-0.08	0.13	0.19	**0.91**	0.23	0.18	0.44
RESP2	-0.14	0.34	0.23	**0.93**	0.16	0.24	0.37
RESP3	-0.07	0.26	0.08	**0.94**	0.23	0.29	0.33
EOU1	-0.11	0.34	0.43	0.22	**0.87**	0.44	0.18
EOU2	-0.12	0.35	0.40	0.20	**0.96**	0.73	0.26
EOU3	-0.04	0.24	0.32	0.20	**0.95**	0.64	0.35
EOU4	-0.13	0.28	0.45	0.21	**0.96**	0.75	0.30
PU1	-0.29	0.26	0.51	0.15	0.64	**0.95**	0.36
PU2	-0.23	0.20	0.42	0.27	0.68	**0.96**	0.39
PU3	-0.24	0.31	0.51	0.23	0.68	**0.96**	0.40
PU4	-0.26	0.27	0.49	0.26	0.67	**0.98**	0.42
PU5	-0.21	0.28	0.51	0.26	0.64	**0.96**	0.37
PU6	-0.17	0.19	0.49	0.27	0.67	**0.96**	0.38
FRQ1	-0.27	0.27	0.30	0.40	0.28	0.33	**0.95**
FRQ2	-0.31	0.16	0.35	0.42	0.31	0.38	**0.95**
FRQ3	-0.41	0.27	0.33	0.39	0.27	0.45	**0.95**
FRQ4	-0.25	0.00	0.33	0.32	0.23	0.33	**0.84**

Table D5: Item-Construct Correlations: Post-Intervention							
	PR2	**TRANS2**	**TVAL2**	**RESP2**	**EOU2**	**PU2**	**FRQ2**
PR22	**0.76**	-0.04	-0.17	-0.26	-0.15	-0.06	-0.13
PR32	**0.82**	-0.06	-0.36	-0.20	-0.15	0.11	-0.29
TRANS22	0.03	**0.94**	0.40	0.10	0.21	0.27	-0.20
TRANS32	0.06	**0.92**	0.44	-0.03	0.19	0.19	-0.18
TVAL12	-0.46	0.53	**0.88**	0.16	0.17	-0.08	0.24
TVAL22	-0.34	0.45	**0.91**	0.13	-0.01	-0.10	0.25
TVAL32	-0.40	0.55	**0.91**	0.17	0.30	-0.01	0.13
RESP12	-0.23	0.10	0.13	**0.95**	0.05	0.00	-0.10
RESP22	-0.23	0.15	0.19	**0.93**	0.08	0.04	-0.12
RESP32	-0.25	0.22	0.16	**0.93**	0.09	0.07	-0.04
EOU12	-0.28	0.15	0.18	0.08	**0.88**	0.32	0.03
EOU22	-0.26	0.26	0.21	0.04	**0.85**	0.43	0.04
EOU32	-0.15	0.22	0.13	0.15	**0.91**	0.38	0.06
EOU42	-0.08	0.20	0.11	0.01	**0.94**	0.42	-0.05
PU12	0.10	0.25	-0.09	0.01	0.45	**0.95**	0.03
PU22	-0.02	0.27	-0.04	0.07	0.41	**0.97**	0.09
PU32	0.04	0.24	-0.11	0.04	0.37	**0.96**	0.16
PU42	-0.01	0.31	-0.05	0.06	0.36	**0.96**	0.14
PU52	0.00	0.32	-0.02	0.11	0.42	**0.94**	0.11
PU62	-0.02	0.19	-0.04	-0.08	0.46	**0.89**	0.15
FRQ12	-0.21	0.07	0.27	-0.03	0.12	0.20	**0.93**
FRQ22	-0.34	-0.03	0.18	-0.06	0.06	0.10	**0.95**
FRQ32	-0.24	-0.02	0.16	-0.17	0.09	0.24	**0.93**
FRQ42	-0.36	-0.02	0.27	-0.09	-0.18	-0.11	**0.83**

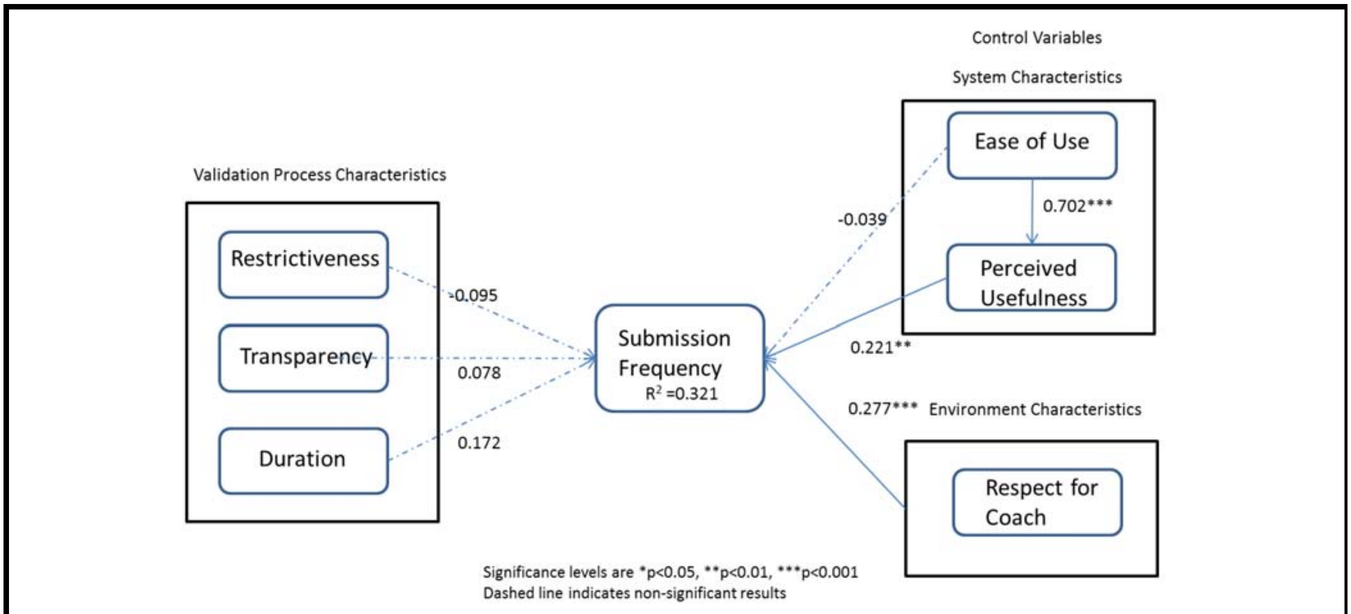

Figure D1. Pre -Intervention Results that Include KMS Characteristics

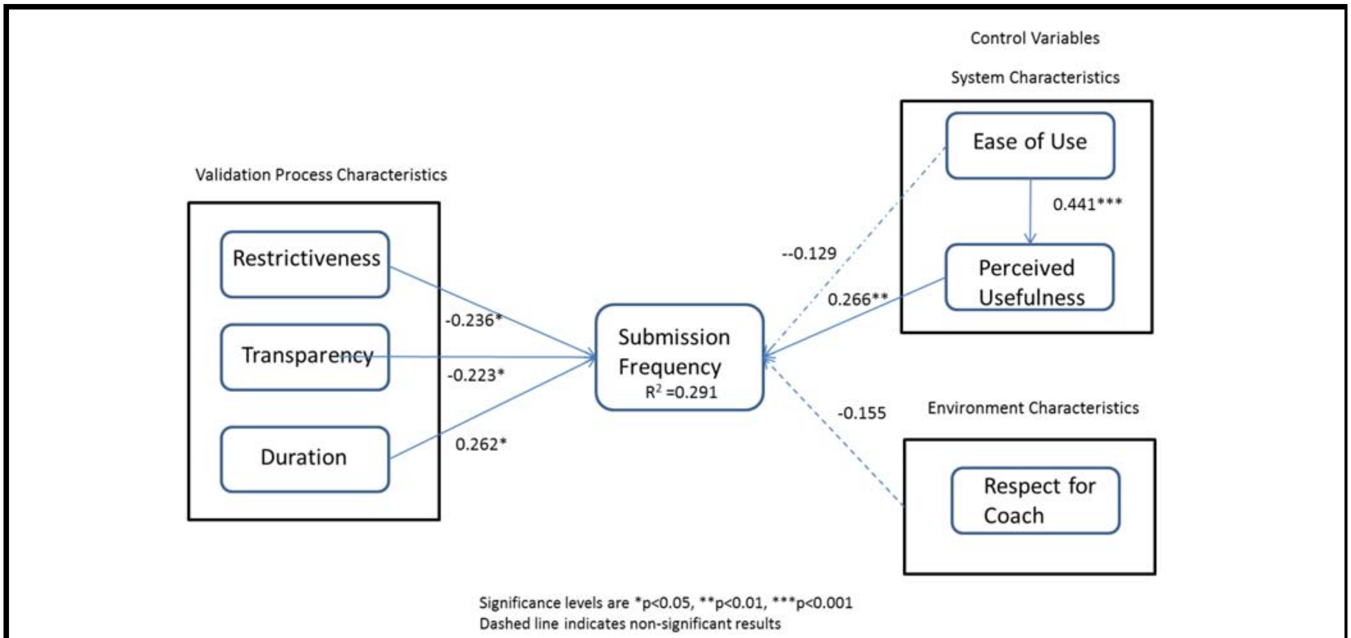

Figure D2. Post-Intervention Results that Include KMS Characteristics

Appendix E

Heuristics for Statistical AR

Table E1. Heuristics for Statistical AR

Stage	Author Considerations	Editor/Reviewer Evaluations
Diagnosing	Carefully describe how the researcher and the client organization work together to diagnose the problem. Identify theory/ies for problem diagnosis and a potential intervention. Leverage the rubric for theory selection (Appendix B). Collect data to evaluate the theory *prior* to the action such that the data can be used in subsequent statistical analyses.	Understand the client organization and the process the authors went through to diagnose the problem. Evaluate the process that the authors have undertaken to identify the theory/ies. More than one set of appropriate theories can exist to diagnose and prescribe for the situation. Ensure that the client has been engaged in this process. Evaluate the data that the authors have collected and its appropriateness for further statistical analyses.
Action Planning	Describe the derivation of the intervention from the appropriate theory/ies.	Evaluate the fit of the selected theories to the problem. Consult the rubric for theory selection (Appendix B). The evaluation at this point is how well the theory/ies are being followed.
Action Taking	Describe how the intervention was carried out and how the identified theory/ies were used.	Evaluate the degree to which the implementation of the intervention derives from the theory/ies.
Evaluating	Carefully describe the data collection that was conducted to test the effectiveness of the intervention. For statistical action research, this should include quantitative data (e.g., data to compare to the pre-intervention data), and/or qualitative data to provide insights into how and why the intervention did (or did not) work as expected.	Evaluate the data collection in terms of its ability to provide insights into the problem and its intervention. Traditional validation techniques might be applied to the quantitative/qualitative data, as appropriate.
Specifying Learning	Integrate the qualitative and quantitative data in order to provide insights for the organization, the problem, and the theories used in the research.	Consistent with other research, this section should be assessed for the degree to which it derives from the data and the theories.

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