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Editorial

Have we controlled properly? Problems with and recommendations for the use of control variables in information systems research

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ABSTRACT

Statistical controls can ensure accurate estimates of causal effects in the evaluation of alternative explanations. However, the research method literature has raised concerns about the appropriate use of control variables (CVs). In this paper, we propose guidelines for the appropriate use of CVs in IS research. We review the use of CVs in statistical control articles published in *MIS Quarterly*, *Information Systems Research*, *Journal of Management Information Systems*, and *Journal of the Association for Information Systems* between 2015 and 2019. We review a total of 298 articles and closely examine 72 of them. On average, the articles used 5.63 CVs; 65.3% of the articles did not provide a rationale for their choice of CVs, 58.3% did not report the reliability and validity of their CVs, and none included CVs in their hypotheses. To remedy this situation, we discuss an article that exemplifies the proper use of CVs in IS research and make six recommendations for the proper use of CVs. For IS researchers, this paper advances the understanding of the proper use and reporting of CVs. For IS journal editors and reviewers, it provides recommendations for evaluating the use of CVs in empirical IS research. Ultimately, the proper use of CVs strengthens causal arguments and may even improve the generalizability of findings.

1. Introduction

Although a study's control variables (CVs) are not its main variables of interest, they are used to rule out alternative explanations for the study's findings (Becker, 2005). CVs are used in a wide variety of disciplines, including psychology (Cinelli et al., 2022; Newcombe, 2003), management (Becker, 2005; Becker et al., 2016; Bernerth et al., 2018; Breaugh, 2006, 2008; Spector & Brannick, 2011), education (Felisoni & Godoib, 2018; Korving et al., 2016), marketing (Deshpande et al., 2000; Verhoef & Leeflang, 2009; Webster et al., 2005), and IS (Ganju et al., 2016; Liang et al., 2007; Ringle et al., 2012). An improperly handled CV can confound the relationships among the variables of interest, thus threatening the validity of inferences drawn from the data analysis. For example, any change in a CV, whether due to manipulation, social desirability bias, or other reasons, could distort the correlation between the independent and dependent variables. Therefore, researchers need to be careful not only about which CVs they include but also about how they use them in their research (Becker et al., 2016; Cinelli et al., 2022; Spector & Brannick, 2011).

IS researchers often have to make difficult choices about how to incorporate controls into their studies. *Statistical controls* allow researchers to collect data in more natural contexts than do experimental controls, thereby increasing the generalizability of their findings (e.g., Carter et al., 2020). Studies have found that in cases in which the use of experimental controls is inappropriate, unethical, or impossible, statistical controls are used to improve the precision of the estimates between the theoretical constructs of interest (Carlson & Wu, 2012; Cinelli et al., 2022; Spector & Brannick, 2011; Wysocki et al., 2022). Notably, all of these studies are from non-IS fields, indicating the need for this editorial to address this issue.

Making good choices about how to integrate CVs is important because it affects the accuracy of estimates of causal relationships as well as the results of tests of alternative explanations (Bernerth et al., 2018; Schmitt & Klimoski, 1991; Spector & Brannick, 2011). The proper use of CVs allows researchers to estimate the "pure" relationship between dependent and independent variables, to measure a controlled relationship between two variables that accounts for the effects of the other meaningful variables, and to infer the contribution of a variable to the prediction of a dependent variable after accounting for the effects of the other variables (Breaugh, 2008; Carlson & Wu, 2012; Cinelli et al., 2022; Spector & Brannick, 2011). In contrast, the improper use of CVs can lead to misleading results. For example, although computer self-efficacy is important (Tams et al., 2018), it may not be an appropriate CV in all IS studies. The methodological and psychological literature has clearly demonstrated why and how CVs should be used in statistical analyses to avoid misleading results (Becker, 2005; Becker et al., 2016; Bernerth & Aguinis, 2016; Cinelli et al., 2022). Without clear guidance in this area, IS studies are likely to encounter problems, such as a lack of justification for inclusion, unclear descriptions of measures and methods, and incomplete reporting (Becker, 2005). Thus, our study provides necessary guidance on the proper use of CVs in IS research.

To the best of our knowledge, there is no domain-specific set of recommendations for the use of statistical controls in IS research. Such

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recommendations will enable the IS discipline to keep pace with best practices in business research, to ensure the proper application of CVs, and to ensure the analytical rigor necessary to build a cumulative IS research tradition. Therefore, the purpose of this editorial is to evaluate the current use of CVs in IS research, to identify opportunities for improving IS research on the basis of our review, and to provide recommendations for improving the use of CVs in IS research, including guidelines for detecting potential CVs. The detection of potential CVs is an emerging topic in the literature of all fields. Providing guidance on the detection of potential CVs will help subsequent studies identify and include appropriate CVs, thus ensuring methodological soundness. To this end, we pose three research questions (RQs):

RQ1. : What types of CVs have IS studies used?

RQ2. : What deviations from the proper use of CVs appear in studies published in leading IS journals?

RQ3. : What is the proper use of CVs in IS studies?

To answer these RQs, we review the use of CVs in empirical articles published in four IS journals—*MIS Quarterly (MISQ)*, *Information Systems Research (ISR)*, *Journal of Management Information Systems (JMIS)*, and *Journal of the Association for Information Systems (JAIS)*—between 2015 and 2019. We do so for two reasons. First, these periodicals are leading IS journals which would be the guidance provided here, while not aiming to criticize the current use of methods in the IS field. Second, the environment affects how we conduct research (Prommegger et al., 2021). The COVID-19 pandemic disrupted normal academic cycles; the data were collected before the COVID period. We analyze and report the data, propose a method for identifying potential CVs, and develop recommendations for the appropriate use of CVs by IS scholars. Our study contributes to the IS literature by identifying the types of CVs and describing their use in four leading IS journals (RQ1 and RQ2). Moreover, by answering RQ3, our study makes four methodological contributions: (1) it explains how to identify a new CV; (2) it provides a clear flowchart for properly designing and conducting research that involves CVs; (3) it promotes the proper testing of old and new CVs in order to understand boundary conditions for their use in statistical models; and (4) it provides guidance for editors' and reviewers' evaluations of the use of CVs in empirical IS research. Overall, our study contributes to the proper use of CVs in IS research.

The remainder of this article is organized as follows. Section 2 reviews the use of CVs in the IS literature; Section 3 describes the current use of CVs in IS research; Section 4 presents our proposed procedures for identifying potential CVs; Section 5 offers six recommendations for IS researchers and discusses an article that exemplifies how to use CVs and avoid confounding results; and the final section presents the study's conclusions and discusses its limitations.

2. Prior research

Appendix A, which lists the reviewed studies and their methodologies, indicates that none of the studies suggested a CV-detection method, which our study uniquely proposes. The takeaways of this appendix are as follows: (1) although many disciplines have reviewed their progress in the proper use of CVs, the IS discipline has not sufficiently done so, and (2) our study's suggestion of a CV-detection method represents a novel contribution to IS research methods. Appendix B summarizes previous studies' recommendations for using CVs; it indicates that Becker et al. (2016) summarized all the studies that preceded their paper and provided comprehensive CV recommendations. Hence, we use Becker et al.'s (2016) recommendations as the foundation for our own. We review the use of CVs in IS research in the following section.

3. The use of control variables in IS research

To assess the use of CVs in IS research, we reviewed the relevant articles published in *MISQ*, *ISR*, *JMIS*, and *JAIS* from 2015 to 2019. These periodicals are flagship journals according to the University of Texas at Dallas lists (*MISQ* and *ISR*), the *Financial Times* 50 list (*MISQ*, *ISR*, and *JMIS*), and the Chartered Association Business School 4 * plus (*MISQ*, *ISR*, and *JAIS*). We searched for "control variable" and "control variables" in *MISQ* and *JMIS* using the EBSCO Host database, in *ISR* using the INFORMS database, and in *JAIS* using the ProQuest database. We located a total of 404 articles: 121 in *MISQ*, 93 in *ISR*, 110 in *JMIS*, and 80 in *JAIS*.

Our review of the IS articles, including their figures and tables, indicated that IS studies have used many CVs, including age (Armstrong et al., 2015; Schmitz et al., 2016; Sykes, 2015; Venkatesh et al., 2017; Ye & Kankanhalli, 2018), gender (Armstrong et al., 2015; Schmitz et al., 2016; Sykes, 2015; Ye & Kankanhalli, 2018), education (Schmitz et al., 2016; Ye & Kankanhalli, 2018), organizational tenure (Sykes, 2015), organizational position (Sykes, 2015), computer self-efficacy (Sykes, 2015), preimplementation levels of job stress (Sykes, 2015), pre-implementation levels of job satisfaction (Sykes, 2015), pre-implementation levels of job performance (Sykes, 2015), tenure (Armstrong et al., 2015; Ye & Kankanhalli, 2018), negative affectivity (Armstrong et al., 2015), individual characteristics (Schmitz et al., 2016), number of previous jobs (Venkatesh et al., 2017), programming skills (Ye & Kankanhalli, 2018), and platform (Ye & Kankanhalli, 2018). Recent studies have included other CVs, including health anxiety (Choi et al., 2022), critical thinking (Kucharska & Erickson, 2023), permission levels (Junglas et al., 2022), and daily Internet use (Gupta et al., 2023).

Many IS researchers feel confident that including CVs will lead to clean results and the discovery of "true" relationships. However, doing so involves potential problems, such as reducing statistical power and available degrees of freedom, and reducing the amount of explainable variance in the outcomes of interest (Becker, 2005; Becker et al., 2016; Carlson & Wu, 2012). For example, Becker (2005) investigated the statistical control of variables in organizational research and identified potential problems such as a lack of justification for inclusion, unclear descriptions of measures and methods, and incomplete reporting. Furthermore, Atinc et al.'s (2012) findings indicated notable enhancements in the use of CVs in management research, and the study demonstrated the appropriate use of CVs for future studies. IS researchers are likely to confront analogous challenges when incorporating CVs into their studies. By employing similar approaches, our study offers a valuable resource for leveraging CVs more effectively in IS research. For this reason, we adapted the CV criteria developed by Atinc et al. (2012) and Becker (2005) to investigate the potential problems associated with the use of CVs in articles published in the leading IS journals.

To compare the results of our literature review with those of methodological studies in organizational and management research, we focused on statistical control in correlational studies, that is, studies using hierarchical regression and structural equation modeling (SEM), because these are the most commonly used methods for evaluating cause–effect analyses. Accordingly, we excluded studies that claimed to be experimental or that did not report correlations. After careful screening, a total of 93 articles on statistical control in correlational studies were identified: 25 in *MISQ*, 15 in *ISR*, 30 in *JMIS*, and 23 in *JAIS*.

Appendix C lists the 93 articles included in our review, along with the CVs they employed. We classified these articles based on their research design, research method, findings, and discussion (Atinc et al., 2012; Becker, 2005). For each article, we checked and recorded (1) the number and name of the CVs; (2) whether the CVs were used in a section title; (3) whether the CVs were accompanied by either a theoretical justification or prior empirical evidence; (4) whether the CVs were included in the hypotheses, as stated in terms of residual substantive variables and sign prediction of the CV on the dependent variable (DV) (e.g., CV-DV); (5) whether the CVs were described in the results section, the type of the CVs (proxy or not), the descriptive statistics for the CVs, the provision of reliability and validity for CV measurement, and the inclusion of the CVs in correlation analyses; (6) whether the CVs were discussed in the discussion section; and (7) whether potential CVs were challenged and identified. Table 1 summarizes our findings and compares our results (based on the 93 IS articles) with the results of Becker (2005) and Atinc et al. (2012).

3.1. Descriptive statistics for control-variable use in IS research

The 93 articles used an average of 5.72 CVs, with a standard deviation of 3.66. This was consistent with the number of CVs used in articles in other fields. For example, extant micromanagement studies used an average of 4.48 CVs, with a standard deviation of 2.63, whereas the extant macromanagement studies used an average of 10.24 CVs, with a standard deviation of 7.45 (Atinc et al., 2012). The number of CVs per study in the four IS journals we reviewed was similar to the number of CVs per study in organizational and management research. The CVs used in IS research were age, gender, education, income, firm size, computer skills, trust, tenure, work experience, fear-appeal-message type, organizational position, IT industry, negative affectivity, platform, programming skills, collectivism, power distance, uncertainty avoidance, loss due to security attacks, features, sensory requirements, team size, team expertise, team experience, design availability, reuse, number of jobs, behavioral intention, facilitating condition, preimplementation job performance, rank, computer experience, conscientiousness, expertise, change management, support, training satisfaction, perceived ease of use, perceived usefulness, loss of knowledge power, codification effort, organizational reward, image, reciprocity, and more. The studies reported these CVs as contextual factors.

Table 2 presents some examples of the CVs used in the IS papers. This table can help IS researchers consider which CVs are appropriate for their studies and determine whether their studies are missing relevant CVs.

3.2. Rational selection of CVs

The majority of the articles (60%) did not devote a separate section to CVs. In Atinc et al. (2012), by contrast, this percentage was 24.7%, indicating that the IS field currently does not consider CVs a pressing issue. The use of CVs has undergone development and improvement in organizational and management research but not in the IS discipline. Furthermore, 87% of the articles used primary data, 6.5% used secondary data, and 6.5% used both primary and secondary data. Among the articles, 42% provided a rationale for the inclusion of all of their CVs, 20.4% provided a rationale for the inclusion of some of their CVs, and 42% provided no such rationale for any of their CVs. Of the articles, 78.5% did not provide a theoretical justification for the inclusion of any of their CVs, only 10.75% did so for the inclusion of some of their CVs, and only 10.75% did so for the inclusion of all of their CVs. These results are consistent with the findings of Bernerth and Aguinis (2016), whose review of top management journals found clear theoretical justifications for the inclusion of CVs in only 5% of the articles published in 2003 and 3% of the articles published in 2012. These findings show that IS research has devoted little attention to the use of CVs; thus, there is room for improvement in the use of CVs by IS researchers. This shortcoming may be due to IS researchers' lack of familiarity with or failure to recognize the need for clear theoretical justifications of the inclusion of CVs.

Regarding prior empirical evidence, 28% of the 93 IS journal articles included citations or evidence in support of all of their CVs, 50.5% did so for some of their CVs, and 21.5% included no such citations or evidence. That is, most of the studies provided citations or evidence in support of their CVs (78.5%). These results show that IS researchers are aware of the need to cite previous studies in support of their inclusion of CVs.

Regarding CV type, 23.6% of the articles used only proxy CVs, 49.5% used some proxy CVs, and 26.9% used no proxy CVs. In short, most of the articles (73.1%) used at least one proxy CV. These findings may reflect scholars' incomplete understanding of the implications of using proxy CVs; doing so can confound analyses and lead to inaccurate interpretations (Spector & Brannick, 2011).

3.3. Inclusion of control variables in hypotheses

As Becker et al. (2016) suggested, CVs should be included in hypotheses and models when it is feasible to do so. Excluding CVs from hypotheses permits researchers to test their hypotheses without accounting for the relevant CVs, which brings the risk that they present results without controlling for the influence of CVs. While this would allow readers to assess the effect of the rest of the model beyond the CVs, it does not fully explain the impact of including CVs or not in the analysis. We therefore checked for the inclusion of CVs in the hypotheses of all the IS articles we reviewed. None of the articles included CVs in their hypotheses, and none predicted the CV-DV sign. This result is consistent with the findings of Atinc et al. (2012); that is, only 3.6% of the papers they reviewed mentioned CVs in their hypotheses. The tendency to exclude CVs from hypotheses may be due to researchers' lack of awareness regarding the importance of including CVs in hypotheses and predicting the CV-DV sign. Testing hypotheses in the absence of CVs is inconsistent with the emerging standards for the rigorous use of CVs in scientific research. Becker et al.'s (2016) proposal has the potential to bring about a significant shift in the IS field's prevailing practice in this area, that is, a shift away from omitting CVs from hypotheses and toward including them.

3.4. Justification of measurement and control methods

Most of the articles provided justifications for their CV measurement and control methods. In total, 72% of the articles mentioned their CVs and how they were measured, whereas the remaining 26.9% mentioned their CVs without specifying how they were measured. The findings of Atinc et al. (2012) indicated that 90% of their reviewed papers named their CVs and clarified how they were measured. Our results show that IS researchers still need to address this issue. Furthermore, most of the 93 articles identified their control methods and provided justifications for choosing those methods; that is, 79.6% clarified their control methods. Only 15% of the 93 IS articles did not identify or provided unclear identifications of their methods; similarly, in Becker (2005), this percentage was 8.8%. According to the methodological literature, clarifying the control methods in IS articles is positive and adds clarity to the analysis (Atinc et al., 2012; Becker, 2005).

3.5. Reporting and discussing the control variables

All 93 articles (100%) used CVs, and most of them (64.5%) discussed their CVs in the results section, whereas 35.5% did not discuss their CVs at all. Atinc et al. (2012) found that 60.9% of the articles they reviewed discussed their CVs in the results section. This means that IS research is slightly better than other management fields in this respect. In terms of descriptive statistics for CVs, most of the articles (67.7%) provided means and standard deviations, whereas 32.3% did not. Atinc et al. (2012) found that 86.3% of the articles they reviewed provided means and standard deviations. The means and standard deviations of CVs should be reported (Atinc et al., 2012; Becker, 2005) because they may provide information about the central tendency and dispersion of CVs and indicate opportunities for future meta-analytic work on IS topics.

Of the articles that were able to assess the adequacy of CV measurement, only 37.6% reported CV reliability and validity results, whereas 62.4% did not. Researchers should report such results because adequate CV reliability and validity are essential for validating research findings (Becker, 2005; Becker et al., 2016). The majority of the studies (61.3%) included their CVs in the correlation table, whereas 38.7% did not. Of the management studies they reviewed, Atinc et al. (2012) found

Table 1
Results Concerning CV Use and Comparisons with Previous Studies.

Area	Coded Variable	Value	Becker (2005)	Atinc et al. (2012)	This Study
Rational selection of CV	Separate section for CV	Yes	X	75.2%	40.0%
		No	X	24.7%	60.0%
		Total	X	100%	100.0%
	Source of data	Primary	X	53.6%	87.0%
		Secondary	X	36.5%	6.5%
		Both	X	9.7%	6.5%
		Total	X	100%	100%
	Basis for inclusion (no rationale)	No explanation for any CV (Becker, 2005)	18.3%	18.2%	42.0%
		No explanation for at least one CV (Becker, 2005)	33.3%	X	20.4%
		Unclear explanation(s) (Becker, 2005)	63.3%	X	X
		Clear explanation	X	X	37.6%
		Total	X	X	100.0%
	Theoretical rationale or prior empirical evidence	Citations/evidence for at least one variable	X	53.8%	6.5%
		Citations/evidence for all CVs	X	19.7%	28.0%
		No citations/evidence for at least one variable	33.3%	X	44.0%
		No citations/evidence for any CV	35%	26.5%	21.5%
		Total	X	100%	100.0%
	Justification for inclusion	Full	X	X	34.4%
		Partial	X	X	23.7%
		None	X	X	41.9%
		Total	X	X	100.0%
	Proxy CVs	At least one proxy variable	X	X	49.5%
		All proxy variables	X	X	23.6%
		No proxy CVs	X	X	26.9%
		Total	X	X	100.0%
Inclusion of CV in hypothesis	Hypotheses stated in terms of residual substantive variables	CV mentioned in hypothesis	X	3.6%	0.0%
		CV not mentioned in hypothesis	X	96.4%	100.0%
		Total	X	100%	100.0%
	Sign predicted	Prediction of CV-DV sign for at least one variable	X	12.2%	0.0%
		No prediction of CV-DV sign	X	87.8%	100.0%
		Total	X	100%	100.0%
Methods	Clarity of measure for CVs	No information at all	X	3.6%	1.1%
		Names for the variables	X	6.4%	26.9%
		Names for the variables and descriptions of how they are measured	X	90%	72.0%
		Total	X	100%	100.0%
	Basis for and clear explanation of method of control	Missing or unclear identification of method	8.3%	X	15.0%
		Missing or insufficient explanation for the choice of method	28.3%	X	5.4%
		Clear identification of method	X	X	79.6%
		Total	X	X	100.0%
Results (reports)	Discussion of CV in results section	Discussion of CV in results section	X	60.9%	64.5%
		No discussion of CV at all	X	39.1%	35.5%
		Total	X	100%	100.0%
	CV-DV sign as predicted	Outcome as predicted	X	8.8%	2.2%
		Outcome not as predicted or no prediction made	X	91.2%	97.8%
		Total	X	100%	100.0%
	CVs per study (total)	For M (mean), SD (standard deviation)	X	X	5.72 (3.66)
	Descriptive statistics for CV	M or SD for CV	X	86.3%	67.7%
		No M or SD for CV	21.7%	13.7%	32.3%
		Total	X	100%	100.0%
	Adequacy of measurement for CV	Reliability & validity for CV	X	X	37.6%
		No reliability & validity for CV	46.7%	X	62.4%
		Total	X	X	100.0%
	Correlations for CV	No correlation table	X	0	0.0%
		CV in correlation table	X	89.5%	61.3%
		CV not in correlation table	X	10.5%	38.7%
		Total	X	100%	100.0%
	Type of statistical analysis (multiple methods)	(Hierarchical) linear modeling	X	88.4%	29.0%
		SEM	X	9.4%	71.0%
		Other	X	2.2%	0
		Total	X	100%	100.0%
	Hierarchical regression	CVs first in hierarchical analyses	X	X	81.5%
		CVs not first in hierarchical analyses	X	X	18.5%
		Total	X	X	100
	SEM	Results run both with and without CVs and findings contrasted	X	X	24.2%
		Results not run both with and without CVs and findings not contrasted	X	X	75.8%
		Total	X	X	100%
Discussion (interpretation)	Discussion of CV in discussion section	Discussion of CV in discussion section	X	26.7%	21.5%
		No discussion of CV at all	X	73.3%	78.5%

(*continued on next page*)

Table 1 (*continued*)

Area	Coded Variable	Value	Becker (2005)	Atinc et al. (2012)	This Study
		Total	X	100%	100.0%
	Interpretation of CV	Control (no alternative explanation)	X	X	95.7%
		No control (explain alternative explanation & suggestion future study)	X	X	4.3%
		Total	X	X	100.0%
Detection of potential CVs	Detection of potential CVs	Detection of potential CVs	X	X	0
		No detection of potential CVs	X	X	100.0%
		Total	X	X	100.0%

Note. "X" indicates no value.
Note: 1. Some numbers do not sum to 100% in Becker (2005).
2. Becker (2005) reviewed *Academy of Management Journal, Administrative Science Quarterly, Journal of Applied Psychology, and Personnel Psychology.*
3. Atinc et al. (2012) reviewed *Academy of Management Journal, Journal of Applied Psychology, Journal of Management,* and *Strategic Management Journal*.
4. Our study reviewed MIS Quarterly, Information Systems Research, Journal of Management Information Systems, and Journal of the Association for Information Systems.

that 89.5% included CVs in the correlation table. This indicates that there is room for improvement in future IS research; high correlations between CVs and the independent variable may distort the relationship between the independent and dependent variables, which may lead, in turn, to misleading research findings (Atinc et al., 2012; Carlson & Wu, 2012).

For illustrative purposes, we focused on hierarchical regression and SEM. Of the articles, 29% used hierarchical regression, and 71% used SEM. Of the articles using hierarchical regression, 81.5% included their CVs in the first hierarchical analyses, whereas 18.5% did not. Of the articles using SEM, 24.2% reported results with and without the CVs and contrasted the two sets of results, whereas 75.8% did not. Researchers should report or explain results with and without the CVs and contrast the findings (Becker et al., 2016); without comparative tests of CVs, researchers cannot know whether the variables are truly controlled for, and the research results will consequently be misleading.

3.6. *Interpretation of control variables*

When interpreting results in the discussion section, most of the articles (78.5%) did not mention a CV, whereas 21.5% did. Similarly, Atinc et al. (2012) found that 73.3% of the articles they reviewed did not mention a CV in the discussion section. This tendency may be due to an attitude among researchers that CVs are unimportant for achieving their research objectives. However, we argue that there are three shortcomings related to the lack of discussion of CVs. First, information about CVs can accumulate from one study to the next and eventually help researchers develop reliable knowledge about their effects. Second, the information about CVs can help researchers interpret how much variance of DVs can be explained by the main study constructs compared to the variance explained by the CVs alone. Third, the lack of a comparison between the results of models that include CVs and those of models that exclude them may create the risk of artificially proving that the main results of analysis can be supported only when CVs are included. In short, neglecting the interpretation of CVs can conceal important information and even threaten the validity of the study's results.

When interpreting CVs, 95.7% of the articles treated their research as fully controlled (no alternative explanation). Few of the studies addressed CVs in the discussion section. The first possible reason is that CVs are not seen as a focus of the study. Researchers discuss only their study's important variables and relationships. The second possible reason is that when authors do not include CVs in their hypotheses, they do not perceive a need to discuss them. Finally, the authors of all the studies we reviewed treated their research as fully controlled, so they presumably saw no need to provide alternative explanations for their findings.

3.7. *Identifying potential control variables*

None of the articles attempted to identify potential CVs. This omission may have been due to a tendency among IS researchers to simply follow previous studies and neglect to take new CVs into serious consideration. Since Becker (2005) identified potential problems in the statistical control of variables in organizational research, the use of CVs has received much attention in organizational research. Furthermore, Atinc et al. (2012) not only reviewed the use of CVs but also provided a comprehensive set of criteria for evaluating their use. Both studies provided recommendations for CV use in organizational research, and these recommendations have received many citations (Becker et al., 2016). The criteria developed by Becker (2005) and Atinc et al. (2012) are widely used in the management literature and are comprehensive. Therefore, we based our review of IS articles on their criteria, as their criteria are consistent with other methodological references; thus, our decision to use those criteria is unlikely to bias the comparison.

Table 2
Examples of Control Variables.

Aspect	Definition	Examples
Demographics	Individual features that are used in various contexts	Gender (Sandhu et al., 2023; Venkatesh et al., 2017; Ye & Kankanhalli, 2018), age (Armstrong et al., 2015; Sandhu et al., 2023; Schmitz et al., 2016), education (Schmitz et al., 2016; Ye & Kankanhalli, 2018), marital status (Tomer et al., 2022), income (Li et al., 2023)
Objective contextual features	Objective features that typically pertain to the study context	Tenure (Armstrong et al., 2015; Ye & Kankanhalli, 2018), MTurk tenure (Nwafor et al., 2022), organizational position (Sykes, 2015), platform (Ye & Kankanhalli, 2018)
Subjective contextual features	Subjective features that typically pertain to the study context	Average time spent on social network websites (Yu et al., 2015), number of friends on the primary social network website (Yu et al., 2015), e-health literacy (Liang et al., 2017), proportion of remote work (Islam et al., 2022), permission level of consumer IT (Junglas et al., 2022), ease of use (Bejar et al., 2023; Romanow et al., 2018), usefulness (Romanow et al., 2018), behavioral intention (Sykes & Venkatesh, 2017), normative commitment (Nwafor et al., 2022)
Use experiences or competencies	Features that describe a user's use history or capabilities	Computer self-efficacy (Sykes, 2015), programming skill (Ye & Kankanhalli, 2018), required competence (Peng et al., 2022), prior use experience (Samuel et al., 2022; Tomer et al., 2022), frequency of use (Yu et al., 2023)

4. Detecting potential control variables

According to Becker et al.'s (2016) suggestions, if CVs lack a firm theoretical or empirical grounding, researchers should exclude them (Becker et al., 2016; Carlson & Wu, 2012). Previous studies have shown that including proper CVs is an important means of clarifying the relationships between the independent and dependent variables (Becker, 2005; Becker et al., 2016; Carlson & Wu, 2012). Our review of well-known recommendations for including CVs indicated that most of our suggestions are consistent with those recommendations (e.g., Atinc et al., 2012; Becker, 2005; Becker et al., 2016; Carlson & Wu, 2012). These studies strongly recommended questioning the use of CVs that lacks explicit justification for including in models. However, they did not consider new CVs and thus did not offer any recommendations for detecting them, indicating that our suggestions are novel. Our suggestions for detecting new CVs are important because any research including variables (including CVs) without justification does not make much sense. Researchers should carefully evaluate the role of new CVs in their studies because there is no evidence that they are relevant to statistical control.

The inclusion of CVs has an impact on the relationships between the independent and dependent variables (Atinc et al., 2012; Spector & Brannick, 2011). According to the literature on the statistical control of CVs, they should not have a significant influence on the estimation of relationships between the predictor and criterion variables, such as spurious or confounding relationships (Bernerth & Aguinis, 2016). Although CVs are not the primary focus of researchers, they should be used to clarify the connections between the independent and dependent variables (Carlson & Wu, 2012). If a CV significantly affects the estimation of relationships between the predictor and criterion variables, it may introduce bias into the study's main findings. Similarity, the inclusion of improper new CVs would lead to uninterpretable parameter estimates, erroneous inferences, unreproduceable results, and other barriers to scientific progress.

For the reasons mentioned above, we propose two methods for detecting CVs in correlational studies, one for hierarchical-regression research and the other for SEM research. First, for hierarchical-regression research, researchers should consider CVs with and without theoretical support. With theoretical support or the support of previous research, CVs may be included in the hierarchical regression, usually before the independent variables, to determine the effects of the CVs (Bernerth & Aguinis, 2016). In the absence of such support, researchers must clearly explain why a new CV should have a relationship with the dependent variables in both the focus study and further studies.

To detect the presence of a CV in hierarchical-regression research, a novel approach to handling CVs is required. Specifically, the CVs are typically entered into the hierarchical regression before the other independent variables to determine their explanatory power exclusive of the independent variables (Atinc et al., 2012). In other words, researchers first enter the CVs into a hierarchical regression. They then enter both the CVs and independent variables into the other hierarchical regression. Becker et al. (2016) suggested testing the significance of the differences between corresponding effect sizes in the two analyses. If the effects of the CV do not affect the results of the original model, then a new CV has been identified and can be proposed for inclusion in the study. A practical decision rule is that if the standardized coefficients of the independent variables with CVs and the independent variables without them differ by less than 0.1, then the differences are negligible (Becker et al., 2016).

To detect a CV's presence in SEM research, researchers should seriously consider explaining why a new CV should have a relationship with the dependent variables and/or a correlation with the independent variables. Researchers should consider using our proposed procedures under two conditions: with and without theoretical support. Fig. 1 illustrates the proposed process for identifying a new CV without theoretical support. Researchers should consider testing the measurement model. If the correlations between a new CV and the other variables are high, the researchers have not been able to separate out the CV's effects on the other variables; thus, a CV has not been identified. If the correlations between a new CV and the other variables are low, researchers need to statistically compare structural models with CVs and those without CVs. If the path coefficient and R-squared value show significant differences between such models, then a new CV has not been identified. However, if the path coefficient and R-squared value do not indicate significant differences between such models, a CV has been identified.

Fig. 2 illustrates the proposed process for identifying a new CV when there is theoretical support for it. When there is a theory that suggests including the CVs, they should be included in the initial research model. Theoretical support ensures that CVs will be in the measurement model. If the correlations between a new CV and the other variables are high, researchers should correlate the new CV with the independent variables and conduct an SEM analysis with and without the new CV. Otherwise, it is unnecessary to add this correlation, but the SEM analysis should still be performed. If the path coefficient and R-squared value with the new CV differ significantly from those without it, researchers should present the results without the new CV and provide post hoc alternative explanations (i.e., modify the supporting theoretical reasons). If the path coefficient and R-squared value with the new CV do not differ significantly from those without it, researchers should present the results with the new CV.

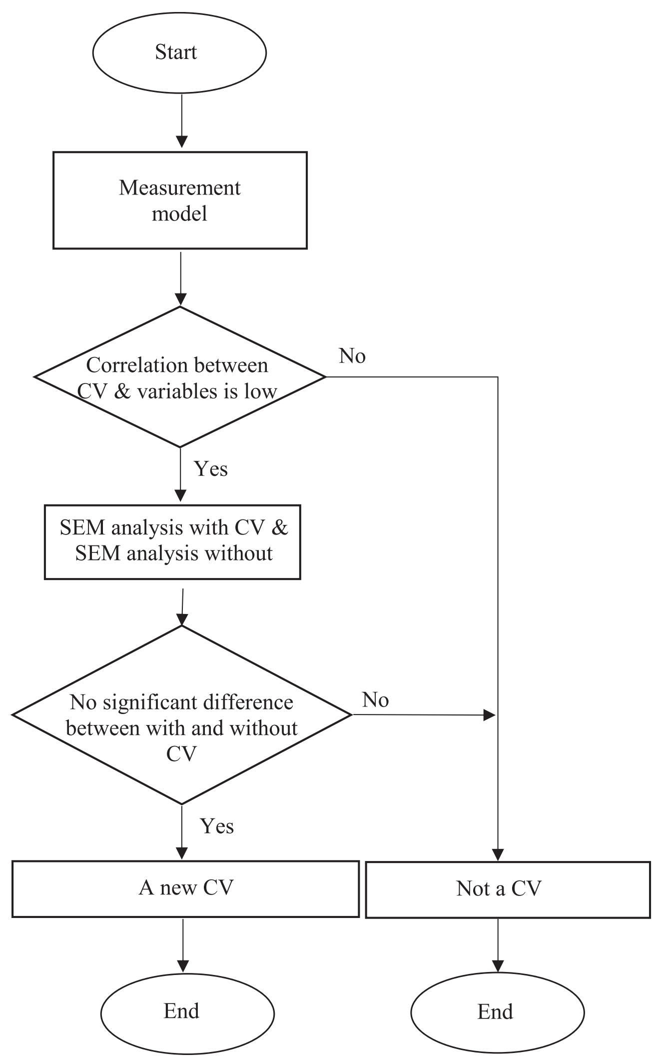

Fig. 1. Flowchart for Detecting a New Control Variable *without* Theoretical Support.

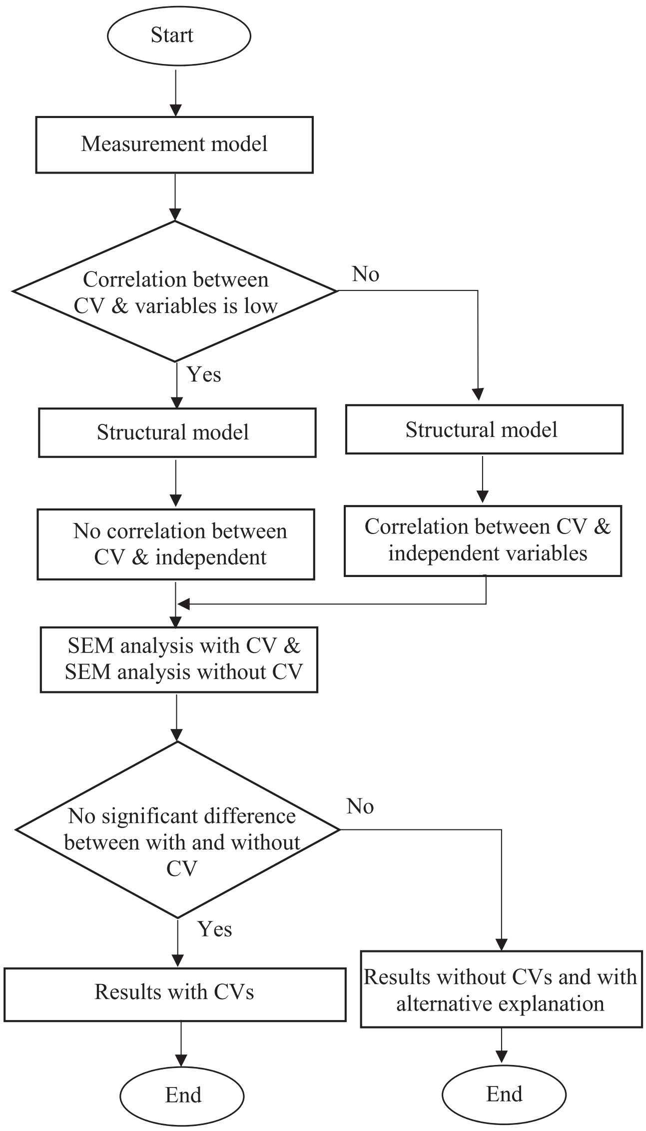

Fig. 2. Flowchart for Detecting a New Control Variable *with* Theoretical Support.

5. Six recommendations for improving the use of control variables

The results presented in Table 2 show that IS research needs to make more effective use of CVs. Papers published in *MISQ*, *ISR*, *JMIS*, and *JAIS* included CVs without rational selection, excluded CVs from hypotheses, failed to report the reliability and validity of CVs, provided incomplete reporting and discussion of CVs, and lacked a proper interpretation of CVs. To address these shortcomings, we offer six IS-specific recommendations that draw on prescriptions in the CV literature (Becker, 2005; Becker et al., 2016; Breaugh, 2008; Carlson & Wu, 2012; Spector & Brannick, 2011).

5.1. *Using theories or previous findings to support the effective selection and inclusion of CVs*

Selecting conceptually meaningful CVs is important because it increases the accuracy of parameter estimation, improves the comprehensiveness of hypotheses, and rules out alternative interpretations. IS researchers need to provide a strong rationale for their choice of CVs. At a minimum, they should explain why their CVs may bias the results and why they need to be controlled (Becker, 2005). In doing so, methodologists should carefully avoid using descriptive or demographic variables, such as an employee’s age as a proxy for career stage or education level as a proxy for the CV, unless they are theoretically relevant (Becker et al., 2016; Breaugh, 2008). For example, if organization size were used as a proxy for large, medium, and small values, it could not be measured directly. Therefore, organization size could not be used to measure the relationship between value and the dependent variable. The challenge of using proxy variables is that the researcher does not really know the strength of the relationship between the proxy and the actual values (Breaugh, 2008). When researchers include proxy variables, they may arrive at results that are very different from the actual CVs’ value (Becker et al., 2016). In conclusion, the use of proxy variables as CVs should be avoided.

5.2. *Use theory to justify the CVs and their roles in the hypotheses*

The use of CVs should be in line with a theory because CVs may capture contextual features, including those associated with a general context (e.g., community care) or a specific context (e.g., a division of an organization in Canada), which are essential to developing contextualized theories (Burton-Jones & Volkoff, 2017). Theoretical arguments about the use of CVs would certainly lead to the inclusion of CVs in the relevant hypotheses (Spector & Brannick, 2011). That is, hypotheses should mention a CV in the context of a direct effect between an independent variable and a dependent variable. For example, Loi et al. (2009) examined four-factor justice and daily job satisfaction and sought to determine the effects of daily interpersonal justice on daily job satisfaction with a CV, that is, daily positive emotions. They offered a good example of how to hypothesize a CV, e.g., daily interpersonal justice is positively associated with daily job satisfaction, after controlling for the influences of daily positive emotions.

However, research articles and research practices have rarely included CVs in hypotheses (Schjoedt & Bird, 2014). Becker et al. (2016) encouraged researchers to include CVs in hypotheses before they test research models. In our view, developing contextualized theory requires IS researchers to provide evidence in support of the inclusion of a CV and the relationships between the independent and dependent variables (Hong et al., 2014). Including CVs in some or all of a study’s hypotheses could clarify the role of CVs in the study and extend the domain-specific understanding of IS-related phenomena. The presence of unsupported CVs suggests a need for future IS research to justify its application in a certain context or domain.

5.3. *Explicitly clarifying and justifying the measurement and control methods for CVs*

All researchers agree that independent and dependent variables require clear measurement, including a name, a scale, and a method of measurement. IS researchers should apply the same requirements to CVs. In this way, a good scale measurement of a CV will have a positive effect on the validity of the research findings. Therefore, IS researchers should provide a name, a scale, dummy coding, a method of measurement, etc. for CVs, just as they do for the other variables in a model (Atinc et al., 2012; Becker, 2005; Straub, 1989).

5.4. *Reporting descriptive statistics and psychometric properties of CVs*

Proper reporting of CVs enriches the understanding of their

Table 3
Suggestions for Improving the Use of Control Variables.

Suggestions	Explanations
Using theories or previous findings to support the selection and inclusion of CVs	The authors provide citations or evidence in support of all their CVs. It is recommended to provide theoretical justifications of the inclusion of the CVs. A separate section that concisely justifies the inclusion of CVs and clarifies the theoretical role of CVs in the study is optimal.
Clearly label the CVs and their effects in the hypotheses	Because previous studies have demonstrated significant effects of CVs, the authors should mention the CVs and the predicted sign in their hypotheses.
Explicitly clarifying and justifying the measurement and control methods for CVs	The authors should clarify how their CVs are measured and why they are measured as such. This valuable information would enable scholars to replicate the study. Moreover, gender and education are proxy variables. It is recommended to avoid using proxy variable if possible.
Reporting descriptive statistics for and psychometric properties of CVs	The CVs are also variables in the research model. Hence, means and standard errors could indicate the central tendency and dispersion of the CVs. It is recommended to provide such information to readers.
Explaining the effects of CVs and discussing their meanings	Only reporting the statistical testing result of CVs is not enough. It is recommended to report the effect size and the predicted CV-DV sign in the results section, thus showing the effects of controlling the CVs and that the effect was as anticipated.
	The CVs should be discussed, particularly in the discussion section. This is especially necessary for CVs that have significant effects. If the authors have theoretical reasons for including these CVs and if the effects were not as predicted, the authors may provide alternative explanations in the discussion section or cautionary statements in the limitations section.
Using our CV-detection method for identifying new CVs	Because researchers may believe using CVs without theoretical or empirical support is necessary, they should identify and justify why they use a new CVs and explain how they detected that new CVs.

psychometric properties, strengthens the potential for replication, and enables a comparison between the results with CVs and the results without them (Becker et al., 2016). In addition, correct reporting of CVs indicates good reliability and validity that a study has. In descriptive statistics, researchers take CVs as independent and dependent variables by reporting their means and standard deviations. In correlations, researchers should report variable correlations with and without a potential CV. If the standardized coefficients of an independent variable with and without CVs have differences of less than or equal to 0.1, this variable is identified as a CV (Becker et al., 2016). In regressions, CVs should be entered into the hierarchical regression before the other independent variables (Atinc et al., 2012; Tabachnik & Fidell, 2001). Researchers should demonstrate the explanatory power of the CVs in model 0 and consequently present the independent variables entered into the hierarchical regression in models 1, 2, and 3, as appropriate. Researchers should report the path coefficients of all the relationships and the explanatory power of all the models.

Future studies should indicate how the inclusion of CVs affects their analytical results. For example, in an SEM analysis, researchers should run the research model twice, once with and once without CVs. Comparing the two sets of results would ensure that there are no significant differences between the model with CVs and the model without them. To further elaborate on the implementation steps, we follow Anderson and Gerbing's (1988) two-step approach to SEM. First, the measurement model correlates CVs with all the other variables. Researchers should present the correlations and the reliability and validity of the constructs. The CVs must meet the standards of reliability and validity (Gefen et al., 2000; Gefen et al., 2011). Second, the structural model should include an SEM analysis with CVs and an SEM analysis without them. Based on theory, empirical studies, logical arguments, and/or hypotheses, CVs have the potential to relate to the dependent variables. Researchers should follow a two-step approach. The first consists of the SEM analysis without CVs, and the second consists of the SEM analysis with CVs. There should be no significant changes between the model with and the model without CVs. Similar approaches could be used in other analytical approaches, as long as the reporting is transparent in teasing out the effect of CVs.

5.5. Explaining the effects of CVs and discussing their meanings

A proper interpretation (i.e., discussion) of a study's CVs will demonstrate whether the study has controlled for the CVs. If the CVs do not affect the results, there is no need to provide an alternative explanation; if they do, researchers need to present alternative explanations. In regression analyses, researchers also need to determine and explain the meaning of the residual predictor values used to test the hypotheses so the results can be interpreted in the context of the residual predictor. For hierarchical-regression results, researchers need to consider the CVs in terms of the size and direction of the effects and the levels of statistical and practical significance. In addition, if researchers identify a new CV, they need to discuss its academic and practical significance. In SEM analyses, researchers should discuss the differences between the model with CVs and the model without them. The absence of significant differences will make interpretation much easier. Researchers can explain the controlling effect of CVs and focus on the results of the original research model (without CVs). The presence of significantly different results indicates that the CVs do not have a controlling effect, that is, they can influence the modeled relationships.

In future research, if a model has theoretical or empirical support, IS researchers need to explain why their CVs have implications for the research model and to note that the results of both model analyses deserve attention. In addition, when researchers identify a new CV, they need to discuss its academic and practical significance and to note that the CV deserves the attention of future studies. An effective discussion of CVs clarifies how their inclusion could improve the accuracy with which the study estimates the relationships between the independent and dependent variables, mitigate the effect of confounding variables, and strengthen the potential for replication.

5.6. Using our CV-detection method for identifying new CVs

Researchers often identify CVs without theoretical or empirical support. Inappropriate inclusion of CVs could distort the results because including them can change the coefficients (meanings) of the relationships (Breaugh, 2008; Williams et al., 2009). In such cases, CVs should not be used. Spurious correlations or causal relationships can affect the original correlated or causal value (Spector & Brannick, 2011), thereby reducing the validity of the results.

Therefore, in future studies, IS researchers should introduce CVs only when they have theoretical or empirical support. In this study, we present two methods for detecting new CVs. Rigorously vetting novel CVs will clarify the relationships between variables and strengthen the validity of its use in future work. Therefore, when researchers have questions about the use of CVs, they should explicitly identify the CV, explain its inclusion, and illustrate its value in a model.

To make the application of our guidelines transparent, we spotlight an article that exemplifies the proper use of CVs in IS research. Tripp et al.'s (2016, p. 296) high-quality paper "Job Satisfaction in Agile Development Teams: Agile Development as Work Redesign" used six CVs: negative affectivity, age, organizational tenure, gender, education, and total work experience. The authors introduced the study's CVs as follows:

> "Because research has shown job satisfaction to be one of the best predictors of turnover intention (Griffeth et al., 2000), we examined several of the control variables that IT turnover studies have often used and chose age and organizational tenure (Ahuja et al., 2007; Joseph et al., 2007; Moore, 2000), negative affectivity (Moore, 2000) and gender and education (Joseph et al., 2007). Studies on job attitudes in the psychology literature have also used gender, tenure, and age as control variables (von Hippel et al., 2013). Additionally, we also included total work experience as a control variable to account for the possibility that the culmination of a developer's total work experience might impact their job satisfaction."

They continued (pp. 283–284): "These variables explained 20% of the variance of job satisfaction. However, inspecting the analysis suggested that only negative affectivity and gender significantly related to the dependent variable." Moreover, the authors stated: "Also, in our final model, negative affectivity was the only control variable that significantly related to job satisfaction."

Tripp et al. (2016) provided or cited evidence for all of their CVs, presented a clear explanation for the inclusion of the CVs, named the CVs, clarified how the CVs were measured, demonstrated the CVs' reliability and validity, presented the CVs in a correlation table, and ran the results with and without the CVs and contrasted the two sets of results.

After reviewing Tripp et al. (2016) as an example, we summarize our suggestions for improving the use of CVs for the IS discipline and explain their logic in Table 3.

Venkatesh et al.'s (2019) examination of parent–child relationships also exemplifies the effective use of CVs. Drawing on attachment theory, the authors hypothesized that five distinct parenting behaviors—parental control, monitoring, unstructured time, dissuasion, and rationalization—influence Internet addiction among children. They not only provided citations in support of their CVs but also specified the CVs, outlined the methods for their measurement, demonstrated their reliability and validity, presented them in a correlation table, and compared the results with the incorporation of CVs and those without the incorporation of CVs. The authors stated that adding the CVs improved the credibility of their results. We urge authors to consult the use of CVs by Tripp et al. (2016) and Venkatesh et al. (2019) to enhance the reliability and validity of their own research findings.

6. Conclusion

When IS researchers include CVs in their studies, they need to select, measure, report, and interpret CVs with care. Our study reviews the articles on the use of CVs as statistical controls, published in leading IS journals (*MISQ*, *ISR*, *JMIS*, and *JAIS*) between 2015 and 2018, clarify the CV types and the issues concerning their application in IS research and provide recommendations for addressing these issues through research design, methodology, results reporting, and discussion.

Because our study provides recommendations for IS scholars, it has a large potential audience. In addition, it could change the way editors and reviewers evaluate the use of CVs in articles and consequently the way scholars use CVs in their papers. This means that the magnitude of the changes our study may bring about is potentially very large. Based on Bergh et al. (2022) (their Fig. 1), the methodological contribution of our article should be substantial.

However, the inclusion of CVs that have no statistical-control purpose is likely to confound the estimation of true relationships in the research model. Therefore, studies need to take CVs as seriously as independent and dependent variables. Furthermore, if researchers do not include CVs in their hypotheses, they should not test hypotheses and report results with CVs. In other words, researchers should match hypotheses and test results (Becker, 2005). We have proposed new methods for detecting a CV with and without theoretical support. This is important because the inclusion of a CV should be based on contextualized theory and evidence, not only on previous research that has found a significant relationship. Finally, we offer six recommendations for researchers. These recommendations could help researchers achieve rigorous and meaningful research outcomes through the appropriate use of CVs.

Our recommendations are useful for both IS authors and editors and reviewers of IS journals for four reasons. First, editors, reviewers, and authors need to recognize that the inclusion of inappropriate CVs diminishes the accuracy of estimates of random effects and does not serve the goal of refining the results by excluding alternative explanations (Cinelli et al., 2022; Wysocki et al., 2022). Editors and reviewers should not insist that authors include controls in their analyses unless they have a solid justification for including CVs. Second, editors, reviewers, and authors need to determine whether the CVs under consideration have theoretical or empirical support. If editors and reviewers have concerns about potential CVs, they should ask authors to explain why and justify why the potential CV is really a CV or if it merits additional theoretical development. Third, hypotheses lead to tests. Where possible, authors should be asked to include CVs in their hypotheses and analyses. Fourth, authors should be asked to present results with and without CVs as well as a full discussion of any discrepancies between the two sets of results. Authors need to thoroughly explain and justify their research design, methods, results, and discussion because appropriate statistical control will improve the accuracy of the study's results and interpretations.

Like most studies, ours has limitations. One limitation is the relatively brief period from which the reviewed papers were drawn. Future studies could include a longer period (e.g., 2003–2023). Such an endeavor could provide evidence that the IS discipline's use of CVs in quantitative research has improved over time. Another limitation is the focus on empirical research. Future studies could examine the proper use of CVs in econometrics research or covariates in experimental research.

CRediT authorship contribution statement

Wen-Lung Shiau: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Patrick Y.K. Chau:** Conceptualization, Supervision, Writing – review & editing. **Jason Bennett Thatcher:** Conceptualization, Supervision, Writing – review & editing. **Ching-I Teng:** Data curation, Formal analysis, Writing – review & editing. **Yogesh K. Dwivedi:** Supervision, Writing – review & editing.

Declaration of Competing Interest

none.

Appendix A. summary of methodologies of previous CV studies

Article	Discipline of Reviewed Journals	Number of Reviewed Journals	Publication Period	Number of Reviewed Articles	Discussion of Whether Reviewed Articles Proposed a CV-Detection Method
Becker (2005)	Organization and management	Four: *AMJ*, *ASQ*, *JAP*, *PPsych*	2000–2002	60	No
Carlson and Wu (2012)	Organization and management	Three: *AMJ*, *JAP*, *SMJ*	2007	266	No
Atinc et al. (2012)	Organization and management	Four: *AMJ*, *JAP*, *JOM*, *SMJ*	2005–2009	1199	No
Bernerth and Aguinis (2016)	Organization and management	Five: *AMJ*, *ASQ*, *JAP*, *JOM*, *PPsych*	2003–2012	580	No
Our study	Management information systems	Four: *MISQ*, *ISR*, *JMIS*, *JAIS*	2015–2019	404	Yes

Note. AMJ=Academy of Management Journal; ASQ=Administrative Science Quarterly; JAP=Journal of Applied Psychology, PPsych=Personnel Psychology; SMJ=Strategic Management Journal; JOM=Journal of Management; MISQ=MIS Quarterly; ISR=Information Systems Research; JMIS=Journal of Management Information Systems; JAIS=Journal of the Association for Information Systems.

Appendix B. summary of recommendations of previous CV research

Article	Recommendations
Becker (2005)	1. Provide at least a brief explanation for why each CV was selected, including why the variable is a biasing factor rather than a substantive one (per Spector et al., 2000). Wherever possible, also include evidence, or citations of studies that contain evidence, that supports the inclusion of each control in the study. 2. Beware of impotent CVs (i.e., those uncorrelated with the dependent variable). Unless there is reason to believe that an CV is a legitimate suppressor, including an CV that is uncorrelated with the dependent variable in analyses reduces power. 3. Beware the "everything but the kitchen sink" approach. Inclusion of numerous CVs could be misunderstood as methodological legerdemain. To avoid such a misunderstanding, make sure there is a logical reason or prior evidence (or both) for including each CV, and do not include impotent CVs. 4. Clearly and concisely describe how each CV was measured and why it was measured in that way. 5. Whenever a less common method of statistical control is used (e.g., in covariance structure modeling, the incorporation of an CV into the dependent variable), take care to precisely describe the method and why it was used. 6. If certain CVs were included in some analyses but not others, or some are treated differently than others in the same analyses, provide an explicit rationale for the differences. 7. Report standard descriptive statistics (e.g., means and standard deviations) for all continuous CVs, including those controlled via incorporation into the dependent variable. In addition, provide summary descriptive statistics for categorical CVs (e.g., the percentage of observations in each category). Wherever possible, supply evidence for the reliability and validity of CVs. 8. Show correlations for all continuous and dichotomous CVs. 9. For categorical CVs with more than two levels, provide a summary of the relationships with the other variables, especially the dependent variable. For example, regress the dependent variable on the categorical MCVs and report the R^2 and betas for the categories. 10. In reporting the primary findings, treat the CVs just like the independent variables; for example, in a regression, include all the CVs (continuous and categorical) in the table(s) of results, and report their betas and significance levels. 11. Run and report the primary results both with and without the CVs. If the two sets of results do not differ, authors and readers can rule out the controls as a potential explanation for the findings. If the results differ, this calls for further study of the role of the controls in the phenomenon of interest. In the former case, only the analyses without controls need to be reported, along with a sentence such as "Analyses were repeated controlling for [the set of controls], but the results were essentially identical." In cases in which there is a significant difference between the results with CVs and the results without them, both sets of analyses should probably be reported, and the difference should be discussed. 12. The results of a study often depend on what CVs are included in the analyses. Therefore, where possible, researchers should follow the lead of several prior studies (e.g., Judge & Bono, 2000) and include CVs in hypotheses (e.g., "Controlling for variables A, B, and C, the higher the level of X, the lower the level of Y"). At the very least, interpret and discuss the results vis-à-vis the CVs included in a given study. This will normally be more meaningful if Recommendation 11 is followed.
Carlson and Wu (2012)	1. **Adopt a Conservative Stance Regarding the Use of CVs** Adding more CVs does not make a study more rigorous. Unless it is very clear that including a specific CV accomplishes an unambiguous and meaningfully statistical control objective, studies that incorporate CVs may confound, rather than enhance, the interpretation of findings. When in doubt, leave them out. 2. **Offer a Complete Reporting of CV Methods (**Becker, 2005**)** Present the reason(s) for using CVs. Identify the specific CVs to be included. Ambiguous justifications should be avoided. 3. **Align Methods/Analysis to Purposes** One size does not fit all. Match the selection of CVs, accompanying analyses, and reporting and interpretation of results to the stated purpose. When the effects of CVs meaningfully affect the results, report the results with CVs and the results without them (Becker, 2005). 4. **Report Data for All the CVs Included in the Research Design (**Becker, 2005**)** Report the mean, standard deviation (or other measure of dispersion), reliability (if appropriate), and zero-order correlations with all the other variables for all the CVs in the research design, even if they are not included in analyses. 5. **Review CV Zero-Order Correlations before Proceeding to Data Analyses** Review all zero-order correlations before conducting analyses to highlight CV correlations that may influence findings. 6. **Match the Analysis to the Hypothesis (**Spector & Brannick, 2011**)** If the hypothesis statement indicates a relationship exists between Variable X and Variable Y but does not mention CVs, the appropriate analysis for testing the hypothesis is one that does not include CVs. 7. **Distinguish between Theoretical and Artifact CVs in Hierarchical Analyses** Distinguish between theoretically meaningful CVs (those that provide theory-based explanations) and artifact CVs (e.g., size, gender, industry, company, etc.) that may be associated with dependent variables but provide no explanation for why the association exists. Theoretically meaningful variables (CVs and independent variables) should be given the first opportunity to account for variance in outcomes because they offer explanations. Artifact CVs should be entered last.
Atinc et al. (2012)	1. Authors should provide this level of detail when justifying the inclusion of CVs. Specifically, this means demonstrating how CVs are related to the study variables, that is, indicating whether there is a causal relationship or only a correlation between the CV and a study variable. In addition, authors should specify a direction of relationship between these variables. Further, we recommend, when possible, the citation of empirical relationships that have been found in meta-analyses to support CV use. If meta-analytic results are not available, then authors should be explicit about the relationship found in prior research (i.e., whether it is a correlation, a finding from longitudinal research, etc.). If no prior empirical research guides CV inclusion, researchers should go beyond a

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(*continued*)

Article	Recommendations
	logical explanation of a purported relationship and rely on theory to justify the inclusion of a CV. Such proper justification should help studies avoid confusing CVs with suppressor or moderator variables. 2. Researchers should predict the sign of relationships between CVs and dependent variables when a theory or prior empirical findings indicate a consistent direction of relationship. This encourages thoughtful inclusion of CVs and increases the likelihood that authors will provide a proper basis for inclusion. Further, authors should present the results of the relationships between CVs and dependent variables not only in tables but also in the article's main text. AsBreaugh (2008) noted, interpretation problems may occur when zero-order correlations and regression weights for control–predictor relationships are the opposite of each other. Such unexpected findings may indicate a suppression effect; thus, just as authors would explain such findings in their analyses of substantive variables, they should explain them when they involve CVs. 3. Authors should present the amount of variance explained by the set of CVs in the dependent variables in the tables or the main text. A surprising number of studies in our sample did not provide this information; thus, readers are unable to compare the amount of variance explained by control versus substantive variables. In our dataset, the amount of variance explained by CVs was on average not much smaller than the amount explained by substantive variables. In some studies, the amount of variance explained by CVs was larger than that explained by substantive variables. Under such circumstances, we recommend that authors consider whether it makes sense to examine the CV as a substantive variable. Relatedly, depending on the relationship between a CV and a predictor variable, there may be so much variance shared by the two that the original predictor is not meaningfully represented (Breaugh, 2006, 2008). Thus, reporting the relationship between the CVs and substantive variables in a study can indicate the degree to which the predictor variables share variance with the controls. As a concluding recommendation on this topic, we suggest that authors consider the practical significance of their findings in relation to CVs. That is, if a dependent variable can be adequately quantified (e.g., by dollars of profit), what actual incremental change in the outcome is accounted for by the CVs and substantive variables?
Becker et al. (2016)	1. **When in doubt, leave them out!** Improves the interpretation of results. 2. **Select conceptually meaningful CVs and avoid proxies.** Promotes appropriate statistical control and the valid measurement of CVs. 3. **When feasible, include CVs in hypotheses and models.** Obviates unjustified inclusion of CVs and fosters more thoughtful hypothesis tests. 4. **Clearly justify the measures of CVs and the methods of control.** Discourages proxies and facilitates the interpretation and replication of results. 5. **Subject CVs to the same standards of reliability and validity as other variables.** Fosters construct validity of CVs and increases the accuracy of parameter estimates for the independent variables. 6. **If the hypotheses do not include CVs, do not include CVs in the analysis.** Encourages appropriate hypothesis testing and model specification. 7. **Conduct comparative tests of the relationships between the CVs and independent variables.** Contributes to the understanding of the causal role of CVs and relationships among the other variables. 8. **Run results with and without the CVs and contrast the two sets of results.** More fully reveals the effects of CVs on the relationships between the independent and dependent variables. 9. **Report standard descriptive statistics and correlations for CVs, and report the correlations between the measured predictors and their partialled counterparts.** Facilitates the understanding of the psychometric properties of CVs, enhances the potential for replication, and enables comparison between measured and partialled predictors. 10. **Be cautious when generalizing results involving residual variables.** Improves the assessment of external validity and the practical application of results.

Appendix C. control variables in the reviewed articles

Article	Control Variables
Anderson et al. (2018)	Team size, duration, colocation strategy, team conflict
Armstrong et al. (2015)	Age, tenure in the IS field, gender, negative affectivity
Benitez et al. (2018)	Data standards, network standards, object-oriented methodology, shared knowledge, prior IT integration experience, IT investment, pre-M&A technological relatedness, acquirer's degree of diversification, acquirer size, acquirer industry, prior M&A experience, method of payment, relative target size, business process outsourcing, acquirer's availability of cash
Chan et al. (2019)	Age, gender, education, SNS use, SNS experience, SNS real name registration, self-efficacy in SNS bullying
Chen and Karahanna (2018)	Polychronicity orientation, age, gender, presence of children
Chen and Zahedi (2016)	Collectivism, power distance, uncertainty avoidance, gender, age, education, loss due to security attacks
Chen et al. (2015)	Annual sales, number of employees, number of IT professionals in the organization, industry
Chen et al. (2019)	Age, gender, education, income, distance to nearest primary care, distance to nearest specialized care, perceived healthiness, subjective norm for mobile services, perceived mHealth ease of use, mobile service use, mHealth adoption decision stage
Choi et al. (2015)	Use duration, default
Craig et al. (2019)	Age, gender
Crossler and Posey (2017)	Age, years of experience in general computing, years of experience in Internet use, gender, income, education, compromise
Dong et al. (2017)	Buyer-firm size, supplier-firm size, relationship length, market uncertainty, location difference, industry, IOS size, IOS type, IOS frequency
Durcikova et al. (2018)	Ease of use, perceived usefulness, respect for coach
Feng et al. (2019)	Age, gender, education level, organization size
Furneaux and Wade (2018)	System age, organization size, (whether it is) a commercial system
Gao et al. (2015)	Gender, board, experience, peer rating, population, physician count, rated physician count, median income, (whether it is) urban, (whether it is) large urban
Gerlach et al. (2019)	Internet trust, Internet use, smartphone operating system (OS), age, gender
Gwebu et al. (2018)	Number of prior breaches, customer, finance, health, sensitive, market value divided by book value, number of recorded compromised
Harrison (2018)	Sex, communication process, previously sold online, experience with medium, previous fault victim, monetary sensitivity
Hashim et al. (2018)	Age, gender, frequency of piracy
Hu et al. (2016)	Industry, number of full-time employees, number of IT-department employees, average annual sales, annual IT budget
James et al. (2017)	Gender, age, computer proficiency, Facebook frequency, number of Facebook friends, Facebook session time, Facebook proficiency
James et al. (2019)	Age, gender, frequency of use, length of ownership, device/app proficiency
Jenkin et al. (2019)	Project duration (months), number of primary informants
Kankanhalli et al. (2015)	Age, gender, education level, programming skill, platform, tenure
Karahanna et al. (2018)	Age, gender, Internet experience

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Article	Control Variables
Karahanna et al. (2019)	Urban/rural, market concentration/competition, profit status, critical access, payer mix, teaching hospital
Karimi and Walter (2015)	Firm size, first year of online publishing
Kathuria et al. (2018)	Firm size
Khansa et al. (2017)	Perceived justice, anger, self-efficacy, age, gender
Kim et al. (2018)	Age, gender, tenure of SNS use, frequency of SNS use, perceived price
Kordzadeh and Warren (2017)	Age, gender
Krancher et al. (2018)	Age, gender, grade point average, offline communication, input from other teams, participation, task-oriented communication
Krasnova et al. (2015)	Gender, age, neuroticism, extraversion, social information sharing, number of SNS friends, dispositional envy
Kudaravalli et al. (2017)	Team size, team expertise, team experience
Kuem et al. (2017)	Age, gender, SNS experience, number of SNS friends, addiction
Kulkarni et al. (2017)	Firm industry, firm size, country
Kyriakou et al. (2017)	Designer tenure, design availability, reuse, OpenSCAD, STL, both OpenSCAD and STL
Lai et al. (2016)	Industry type, ownership type, firm age, firm size, time since ERP adoption
Lankton et al. (2015)	Age, gender, disposition to trust, experience
Lee et al. (2015)	Firm size, firm age, organization types, structures, industry growth
Liang et al. (2015)	Perceived usefulness, self-efficacy, age, gender, education, personal innovativeness, years of ERP use
Liang et al. (2017)	Strategy, firm size, environmental dynamism
Liang et al. (2017)	Age, gender, education level, income, employment status, residency location, Web experience, e-health literacy
Lin and Armstrong (2019)	Gender, native language, education, SNS, tenure in the SNS, number of connections, weekly hours spent on SNS, technological features
Lin et al. (2018)	Tenure, system type, project duration
Lowry et al. (2016)	Age, gender, education, employment status, income, hours per day
Lowry et al. (2019)	Age, gender, education level, computer experience, computer use, Internet experience, situational morale belief, work experience
Lu et al. (2015)	Age, gender, position, preperformance
Maruping et al. (2019)	Project duration, team size, team experience, project size
Matook et al. (2015)	Gender, age, country of origin, computer self-efficacy
Mehta and Bharadwaj (2015)	Vendor firm, team size, project duration, project leader's experience, team's knowledge heterogeneity, team's relational capital
Moeini and Rivard (2019)	Risk propensity, project size, experience, method
Ormond et al. (2019)	Gender, age, education, ethnicity, current and expected grade, importance of extra credit, estimated and actual time to complete the experiment
Oshri et al. (2019)	Modularity, interactions of IP requirements with sources of IP capacity, concentration
Ozer and Vogel (2015)	Gender, age, education, job experience, firm size
Pan et al. (2017)	Gender, age, occupation, education, length of experience, frequency of use, relationship status
Pethig and Kroenung (2019)	Age, gender, education, employment, disability
Phang et al. (2015)	Gender, age, education, income, Internet experience, offline participation, user duration in the forum
Pirkkalainen et al. (2019)	Gender, age, IT experience
Robert and Sykes (2017)	Performance expectancy, effort expectancy, social influence
Roberts et al. (2016)	Age, level of managerial authority, education level, organizational tenure, organizational age, size
Romanow et al. (2018)	Average age of team members, perceived usefulness, perceived ease of use, hospital-patient satisfaction, length of stay, team size, within-team physician proportion, cross-nesting index
Salehan et al. (2017)	Age, gender, education, income, intensity of SNS use, hours of use
Sarker et al. (2018)	Gender, care for dependents, experience in DSD, role, country
Saunders et al. (2017)	Gender, (whether it is) a smartphone, (whether it is for) a professional purpose, number of calls, number of phone features used, number of emails
Schmitz et al. (2016)	Features, education, gender, age
Serrano and Karahanna (2016)	Trust requirements, sensory requirements
Spaeth et al. (2015)	Project type, age, nationality, education
Srivastava and Chandra (2018)	Disposition to trust, age, profession, education, gender, preferred virtual worlds
Sun et al. (2019)	Personal innovativeness in IT efficacy, internal and external computer self-efficacy
Sykes (2015)	Age, gender, organizational tenure, organizational position, computer self-efficacy, preimplementation levels of job stress, preimplementation levels of job satisfaction, preimplementation levels of job performance
Sykes and Venkatesh (2017)	Preimplementation job performance, behavioral intention, facilitating conditions
Tam et al. (2019)	Gender, age
Tarafdar and Tanriverdi (2018)	Firm size, industry profile, digitization of customer-facing process, organization's IT risk profile, organization's EIT project management performance, top management's IT awareness, organizational climate for creativity
Teubner and Flath (2019)	Age, gender, individual risk propensity, number of Facebook contacts, WhatsApp use
Tiwana (2015)	Design-rules compliance, clan control, output control, extension complexity, platform specificity, cross-extension dependencies, extension envelopment risk, platform experience, market segment
Tiwana (2018)	App complexity, app age, free app, ad(advertising)-supported, lifetime review count, unrestricted audience, English, platform dummies, extra-ecosystem dependence, platform tenure, developer's platform experience, freemium strategy, organizational modularity, country dummies, app category, technological uncertainty, Δprice(t1→t3), Δrating(t1→t3)
Tiwana and Kim (2016)	Firm size, prior concurrent IT sourcing experience, industry effect, relative project size, IT investment intensity, concurrent IT sourcing longevity, cost motivation
Tong et al. (2015)	Work experience, education, age, system complexity, system commitment
Tripp et al. (2016)	Negative affectivity, age, organizational tenure, gender, education, total work experience
Turel and Qahri-Saremi (2016)	Age, gender, perceived usefulness of Facebook, satisfaction with using Facebook
Venkatesh et al. (2016)	Gender, age, education, income, Internet self-efficacy, need for government service, government staff
Venkatesh et al. (2017)	Age, previous job count
Venkatesh et al. (2019)	Gender of child, gender of parent, age of child, age of parent, marital status, household income, anxiety, depression, loneliness, peer relationships, Internet cost, computer possession, habit, Internet use, family hours, family time commitment, family involvement, family (marital) stressors, family (parental) stressors, work-family conflict, job involvement, job insecurity, work overload, work stress, child's Internet addiction
Winkler and Wulf (2019)	Industry sector, location of headquarters, client size, service orientation, regulatory exposure, horizontal position, vertical position, job tenure
Wu et al. (2015)	Firm size, industry type
Wu et al. (2017)	Age, gender, education level, job title, years of computer experience, system training, personal innovativeness
Yang et al. (2015)	Age, income, education, team size

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Article	Control Variables
Ye et al. (2018)	Age, gender, programming skill, tenure, education, platform
Yu et al. (2015)	Internet self-efficacy, gender, age, years at university, average time spent on SNS, number of friends on the primary website
Zhang and Venkatesh (2017)	Age, gender, tenure, rank, computer experience, computer self-efficacy, conscientiousness, expertise, change-management support, training satisfaction, perceived ease of use, perceived usefulness, loss of knowledge power, codification effort, organizational reward, image, reciprocity, knowledge self-efficacy, enjoyment in helping, trust

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