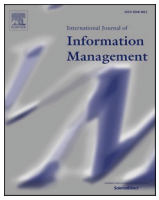
International Journal of Information Management 70 (2023) 102625



Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt



Editorial

Cross-sectional research: A critical perspective, use cases, and recommendations for IS research



ARTICLE INFO

Keywords
Cross-sectional research
Cross-sectional study design
Cross-sectional survey
Cross-sectional survey design
Survey
Survey research design
Causality

ABSTRACT

Cross-sectional data is pervasive in information systems (IS) research. This editorial reviews cross-sectional studies, summarizes their strengths and limitations, and derives use cases of when cross-sectional data is and is not useful in answering research questions. We raise concerns about assertions of temporal causality using data collected employing cross-sectional methods with no temporal order, which makes cause and effect difficult to establish. Based on our discussion of research using cross-sectional data and its limitations, we offer four recommendations for when and how to use such data: (1) improve credibility by reporting research in detail and transparently, (2) ensure appropriate sampling, (3) take configurational perspectives, and (4) integrate cross-sectional data into mixed- or multi-method designs. By doing so, we help IS researchers position and use cross-sectional studies appropriately within their methodological repertoire.

1. Introduction

In order to prepare a tasty dish, a chef needs a clear and good recipe, carefully selected ingredients, and a well-equipped kitchen. The dish's flavor and presentation depend on the chef attending to all three elements of its preparation – following all the proper steps, using high quality ingredients with good flavor, and having all the tools needed to prepare the meal. If the chef skips a step, uses low-quality ingredients, or lacks an essential tool, the dish may well be a failure.

Good research is analogous to cooking. Studies are grounded in clear and solid theory, analyze meaningful data (sets), and apply research methods properly. Numerous Information systems (IS) researchers provide careful guidance on how to develop theory (e.g., contextualization; Hong et al., 2014), advice on how to gather data (Straub, 1989), and when to apply research methods (e.g., qualitative comparative analysis; Mattke et al., 2022; Mattke et al., 2021; Pappas & Woodside, 2021) that can help scholars develop compelling explanations for real-world phenomena. However, if scholars fail to pay sufficient attention to how well different aspects of the research align, e.g., with the research questions and data method, researchers risk overstating conclusions or drawing incorrect inferences.

Data sets are the least elaborated element in IS research. Scholars often fail to sufficiently explain the implications of the data collection technique on theory testing or formally test whether their data meets the quality thresholds needed to conduct analysis. As a result, scholars sometimes rely on sub-optimal data, overuse one form of data collection, or make greater inferences than the data support, an especially great danger with regard to cross-sectional data.

A casual review of research published in major IS journals reveals the pervasiveness of using cross-sectional data. In the *International Journal of Information Management* (IJIM), for example, more than 85 % of papers published from 2020 to 2022 employ a cross-sectional research design. Editors-in-chief of various journals across different subject disciplines have raised concerns about overusing any one form of data collection (Dwivedi, Hughes, Cheung, et al., 2022). One common mistake is using cross-sectional data inappropriately to answer research questions that implicitly or explicitly point to temporal causality (Bono & McNamara, 2011). Consider a research question exploring whether and how beliefs and intentions shape behaviors. Cross-sectional survey data cannot be analyzed to establish causal relationships, but rather only associations between concepts. Temporal causality between beliefs, intentions, and behavior and how variance in beliefs and intentions relate to behavior can be better proven using multi-wave data (Kim & Malhotra, 2005; Kim, 2009).

Since the great majority of IS research attempts to establish temporal causality (e.g., focuses on cause-effect relationships) or assesses how temporal causality evolves over time, and since most recent IS research analyzes cross-sectional data, it is valuable to review the use of cross-sectional data in IS research. In this editorial, we assert the need in IS research to employ multiple research designs, such as collecting data from the same people in two (Shirish et al., 2021) or more (Adamovic, 2022) waves or using experiments to establish causality (Fink, 2022). While cross-sectional data can be analyzed to demonstrate associations between concepts, causality and cause-effect relationships can be demonstrated effectively using research designs that allow for the temporal ordering of variables.

This editorial provides an overview of cross-sectional studies, presents the strengths and weaknesses of using such data, and provides recommendations for conducting cross-sectional research, thus contributing to IS theory and practice. We hope that this critical review of the use of cross-sectional data in IS research will stimulate a broader conversation about data collection practices.

https://doi.org/10.1016/j.ijinfomgt.2023.102625
Received 16 January 2023; Accepted 17 January 2023
Available online 20 January 2023
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2. A brief overview of cross-sectional studies

A cross-sectional study, also known as a prevalence or transverse study, uses a snapshot of participants' beliefs, behaviors, or other variables of interest of a study population (e.g., a group of individuals or organizations) at a specified point in time (Grimes & Schulz, 2002; Hua & David, 2008) to examine research questions (see Fig. 1).

Descriptive and analytical approaches are commonly used in cross-sectional studies (Kesmodel, 2018; Wang & Cheng, 2020). **Descriptive cross-sectional studies** aim to characterize and assess the prevalence or distribution of one or more variables of interest in a population (Aggarwal & Ranganathan, 2019). **Analytical cross-sectional studies** use multiple variables to measure their association within a population using independent samples drawn at different points in time (Ranganathan & Aggarwal, 2019).

Cross-sectional studies can employ single or multiple waves – in that case, with different participants[1] – of data collection (Wang & Cheng, 2020). Many studies draw inferences based on the analysis of **single cross-sectional data**. Others make inferences based on analysis of **repeated cross-sectional data** gathered using surveys administered at successive points in time. This design is called 'pseudo-longitudinal' when the same tools are used to gather data in waves from different participants (Pan, 2021). When collecting data once per month, for example, participants who complete the first cross-sectional survey will not be the same as participants the following month. Such studies can track the prevalence of a variable (e.g., disease) in the population over time.

Cross-sectional data can be gathered using **qualitative or quantitative** techniques (Cummings, 2017). This implies that data are collected, for example, through interviews, focus groups, or questionnaires, and are then further analyzed using regression-based or configurational methods.

3. Strengths, limitations, and use cases of cross-sectional studies

Each cross-sectional approach has strengths and limitations (Fig. 2). We pair these strengths and limitations to offer guidance on when using cross-sectional data is or is not appropriate.

3.1. Strengths: when to use cross-sectional data

The strengths of cross-sectional data help to explain their overuse in IS research. First, such studies can be conducted **efficiently and inexpensively** by distributing a survey to a convenient sample (e.g., the researcher's social network or students) (Compeau et al., 2012) or by using a crowdsourcing website (Lowry et al., 2016; Steelman et al., 2014). Second, using a single cross-sectional design renders collecting all data relatively simple and frees the researcher from worrying about attrition, such that the **whole data set** can be assembled **quickly**. While other types of studies (e.g., cohort study) require the selection of participants based on specific criteria (e.g., depending on participants' status), many cross-sectional studies' **sampling strategy** involves randomly drawing participants from a target population that is relevant for a research study (Martínez-Mesa et al., 2016). These benefits and strengths are illustrated in *four use cases* for when to use data gathered using cross-sectional techniques.

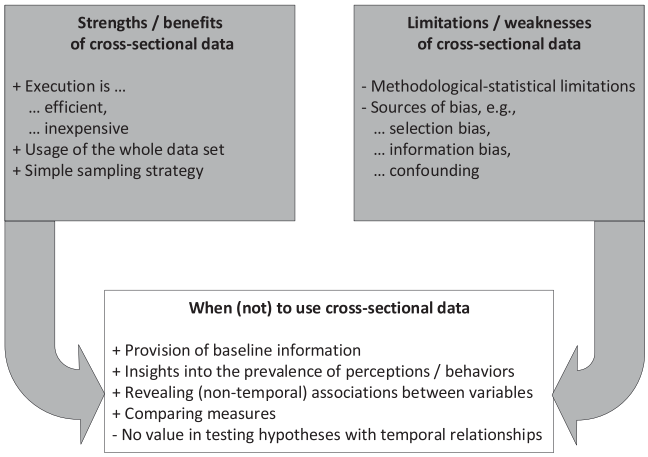


Fig. 2. Overview of strengths, limitations, and use cases (Note: + means positive or indicates when to use cross-sectional data; - means negative or indicates when to not use cross-sectional data).

The first use case for cross-sectional studies is the provision of *baseline information to justify the need for further research on a given topic* (Setia, 2016). Findings from such studies might be used to lay a foundation for more sophisticated follow-up studies or to generate possible hypotheses. Such initial insight helps inform studies of emerging issues or evolving trends, such as the metaverse (Dwivedi, Hughes, Baabdullah et al., 2022), impact of digital technologies on climate change (Dwivedi, Hughes, & Kar et al., 2022) or blockchain applications (Yli-Huumo et al., 2016). For example, as Bitcoin and other cryptocurrencies gathered media attention, research examined variance in investment motivations (Mattke, Maier, Reis et al., 2021), using cross-sectional data to identify different motivations driving the phenomenon. In such cases, cross-sectional data helps inform the design of future research on the phenomena and additional rounds of data collection (e.g., longitudinal data).

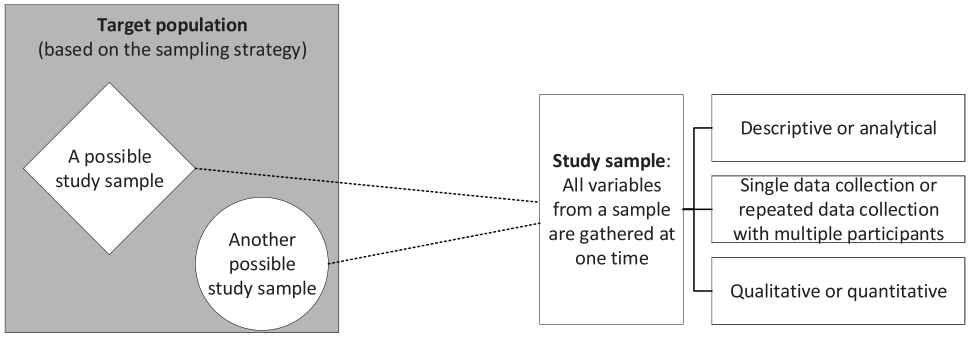


Fig. 1. Characteristics of cross-sectional studies.

A second use case is to establish the *prevalence of perceptions or behaviors* (Kesmodel, 2018; Lu, 2009). Cross-sectional studies offer

[1] In case when the waves are conducted on the same sample, it is a longitudinal design and generates more confidence in causality.

insights into the distribution of variables of interest (e.g., pathological technology use, computer anxiety) which is vital for understanding the impact of a problem within a given target population. For example, one study established the proportion of users who report technostress also report health complaints (e.g., headaches, fatigue) (Gimpel et al., 2018). In that way, such studies can describe the frequency and importance of a problem.

A third use case is estimating (non-temporal) *associations between variables*. Cross-sectional studies reveal how variables are associated with others. For example, research has identified differences between individuals using the social networking site Facebook and those not using it (Ryan & Xenos, 2011). Another study has shown that IT professionals perceive blurring boundaries and work-home conflict as stressful, while non-IT professionals associate these factors less strongly with perceived stress (Maier et al., 2015).

A fourth and final use case for cross-sectional studies is *comparison*. Data from such studies help develop new measures or scales (Compeau et al., 2022), as research might investigate the accuracy of such measurements when comparing new and old measures or establish the factor structure of a measurement model. Similarly, cross-sectional studies offer valuable insights, particularly when paired with data from different sources (e.g., subjective, perceptual data from surveys, and objective data collected during an experiment) to study their association (Junco, 2013; Tams et al., 2014).

3.2. Limitations: when not to use cross-sectional data

While helpful in our use cases, the fact that cross-sectional studies essentially simultaneously gather data on related concepts can be problematic for two reasons: methodological-statistical limitations and bias (see Table 1).

A first limitation is that cross-sectional data suffers from **methodological-statistical limitations** when empirically testing theory. Therefore, it is helpful to have in mind what causality means. Three conditions must be met to establish causality between A and B: temporal precedence (A must temporally precede B), covariation (A and B should covary), and other sources of variation in B should be controlled. In cross-sectional studies, by definition, the first condition is not met. However, an implicit assumption of cross-sectional data is that temporal aspects cannot be addressed (Kelly & McGrath, 1988). Yet, in many theories, time is central to arguments about why and how a cause results in or forms an effect (Cox & Wermuth, 2014). For example, consider the technology acceptance model (TAM; Davis, 1986; Mortenson & Vidgen, 2016), which uses known processes from the theory of reasoned action (Fishbein & Ajzen, 1975). It assumes that the perceptions of ease of use and usefulness result in behavioral intentions to use an IS that, ultimately, form the IS use behavior. Notably, cross-sectional data does not allow for establishing the cause and effect implied by TAM (Levin, 2006; Mann, 2003). This means that the temporal order of perceptions, intentions, and behaviors cannot be reflected, as all data are collected simultaneously. This methodological-statistical limitation of cross-sectional data makes evaluation of temporality between variables of interest impossible.

A second limitation of cross-sectional data is its susceptibility to multiple **sources of bias** that lead to incorrect estimations of the relationship between variables of interest (Maxwell & Cole, 2007; Wang & Cheng, 2020). **Selection bias** occurs when the sample does not represent the population, such that one cannot glean ground truth on the entire target population (Kesmodel, 2018). **Information bias** refers to respondents' tendency to provide socially acceptable answers, rather than providing honest answers, regardless of how socially acceptable they are, and cross-sectional data are specifically prone to that bias as information is typically collected retrospectively (Tripepi et al., 2010). For example, respondents may systematically inflate their performance when asked to recall their use of a tool. **Confounding** is an additional bias. Confounding means that a variable is associated with another variable and influences the outcome variable (Asiamah et al., 2021; Hammer et al., 2009; Lu, 2009). Typically, a confounding variable has three characteristics. First, it is associated with another variable. Second, it is related to the outcome. And third, it is not in the causal pathway between the other variable and the outcome (Wang & Cheng, 2020). While these are effective forms of biases, the literature also discusses specific sub-forms (e.g., recall bias, non-response bias) or other situations that result in incorrect estimations (e.g., Simpson's paradox, survival bias) (Delgado-Rodríguez & Llorca, 2004; Kievit et al., 2013; Tripepi et al., 2010; Wang & Cheng, 2020).

These weaknesses and limitations result in a specific *case* for when *not to use* data gathered with cross-sectional techniques. Lacking a time interval, cross-sectional data has a limited ability to establish temporal causality. Since the data is collected at a single point in time, the cause had no chance to *determine*, *lead to*, or *form* the effect, such that cross-sectional data are usually *not valuable to test hypotheses with temporal relationships*. This problem is pervasive in many studies taking a deductive approach, typically first developing hypotheses based on theoretical arguments and theory and then testing the hypotheses by analyzing data. In developing hypotheses, authors use arguments that have a temporal order in terms of cause-effect-relationships, such that hypotheses typically follow the pattern of "[variable A] *determines* [variable B]," "[variable A] *leads to* [variable B]," or "[variable A] *forms* [variable B]." The temporal order implies the existence of a time interval between measuring both variables. The time interval can range from seconds to years and depends on the context (Kelly & McGrath, 1988), but it is required for the cause to produce an observable effect. Despite the absence of a time interval, many scholars persist in trying to test temporal hypotheses using cross-sectional data.

Table 1
Limitations and shortcomings of cross-sectional research.

Limitations and shortcomings	Meaning	References
Methodological-statistical limitations	With collecting data related to all variables simultaneously as a snapshot, cross-sectional data cannot study the temporal order and the differentiation between cause and effect.	(Levin, 2006; Mann, 2003)
Sources of bias	Multiple types of systematic errors exist when conducting cross-sectional studies, which might lead to incorrect estimations of the true association between variables. Types of such systematic errors include, among others, selection bias, information bias, and confounding bias.	(Hammer et al., 2009; Wang & Cheng, 2020)

4. Recommendations for conducting rigorous cross-sectional research

We offer four recommendations to ensure that cross-sectional data is used appropriately (see Table 2).

The first recommendation points to the need for **detailed and transparent research reporting**. Such reporting includes disclosing the use of cross-sectional data (e.g., in the abstract), formulating appropriate objectives (e.g., referring to relevant practical or theoretical problems), specifying method and findings (e.g., how to reduce biases or handling missing values, providing descriptive data), and comprehensively discuss results and limitations (e.g., external validity, generalizability). Method research in IS and referent disciplines offer guidelines relevant to realizing our first recommendation (Elm et al., 2007; Hui et al., 2019) that could improve the credibility of future research using cross-sectional data. Overall, research should adopt associative rather than causal language, such as "[variable A] *is related to* [variable B]". In

Table 2
Summary of recommendations for cross-sectional research.

Recommendations	Meaning and details
1. Detailed and transparent research reporting	Avoid causal language. Instead, use "is related to". a) Pre-register research b) Offer access to data sets, constructs, meta-data, and syntax c) Increase transparency by offering reviewers access to data d) Make instruments and data collection transparent
2. Appropriate sampling	Explain and follow a reasonable and deliberate sampling process. a) Report the sampling strategy b) Ensure sufficient power to detect effects c) Gather large datasets d) Estimate sample size using analytic methods
3. Configurational perspective	Study causality beyond temporal or cause-effect relationships. a) Conjunctural complexity means that multiple conditions are associated with a variable. b) Equifinal complexity means that multiple combinations are associated with a variable. c) Asymmetry complexity refers to causal asymmetry (i.e., combinations are associated with a variable, but the opposite of that combination is not related to the absence of the variable) and asymmetric relationships (i.e., situations where one specific variable can be associated with another variable with a high *and* low level).
4. Part of mixed- or multi-methods research	Enrich cross-sectional data. a) Follow mixed- or multi-method research designs. b) Use meta-inferences to overcome limitations related to cross-sectional data.

addition, widely accepted research practices need to be followed when using cross-sectional data. First, authors should consider pre-registering their research by specifying their research plan in advance and submitting it to a registry. This involves setting hypotheses based on solid theoretical arguments (Bogert et al., 2021), study design, and data analyses. Second, authors should offer researchers access to the analyzed data set, including constructs and meta-data, as well as the syntax used to conduct main tests (Burton-Jones et al., 2021). Third, authors should provide reviewers, and readers access to their (raw) data to increase research transparency. This prescription is equally relevant to and has been used for (raw) data found in interview transcripts (Helliar et al., 2020), Twitter data (Grover et al., 2018), and empirical survey data (Queiroz & Fosso Wamba, 2019). Fourth, authors should make the instruments and processes used to collect data transparent. This should include the logic used to assign participants to groups. These steps allow readers to understand potential sources of biases in how cross-sectional data were gathered or analyzed.

The second recommendation refers to an **appropriate sampling**. First, the authors should report a sampling strategy that clearly explains what population was sampled and why. It should specify the attributes of the underlying population, and the final sample represents it properly in terms of demography, such as age, gender, and, especially, the variables of interest, such as the role IS plays in their work, their employment status, and their level of IS experience. Second, authors should ensure that cross-sectional studies have sufficient power to detect effects. Authors should calculate sample size requirements based on specific goals (e.g., power, prevalence rate, significance level) and report them. Third, authors should gather large datasets. Even if sample requirements are lean, the passionate ongoing discussion in the IS discipline about sample size and analytic techniques has made it difficult to publish papers with smaller samples (Goodhue, Lewis, and Thompson, 2006; Marcoulides & Saunders, 2006). Fourth, estimates of required sample size should fit the analytic method. Different fit indices (e.g., Cohen's method, RMSEA, Steiger's gamma) should be used that map to the method and research objective (using qualitative data: Marshall et al., 2013; for SEM/PLS: Aguirre-Urreta & Rönkkö, 2015; Kim, 2005; for QCA: Mattke et al., 2022; Mattke et al., 2021; Pappas & Woodside, 2021). For cross-sectional studies, the sample size of descriptive and analytical cross-sectional studies require different calculations (Wang & Cheng, 2020). Wang & Ji (2020) offers a useful resource and specific guidance and their online calculator can be used to estimate sample sizes: http://riskcalc.org:3838/samplesize/).

The third recommendation is to study causality beyond temporal or cause-effect relationships. For example, **configurational perspectives** (Mithas et al., 2022), increasingly used in IS research, offer opportunities to evaluate associations found in cross-sectional data (Mattke et al., 2021). Causality via a configurational perspective is complex; it means it is conjunctural, equifinal, and asymmetric (Mattke et al., 2022). First, conjunctural complexity means that multiple conditions are associated with a variable. For example, a user's perception of technostress is related to the simultaneous combination of numerous personality traits, such as high neuroticism and agreeableness (Pflügner et al., 2021). Second, equifinal complexity means that multiple combinations are associated with a variable. For example, scoring high on neuroticism and agreeableness and low on conscientiousness and extraversion is one specific combination and being high on neuroticism and conscientiousness as well as low on agreeableness and extraversion is another combination that both predispose users to have a high risk of perceiving technostress (Pflügner et al., 2021). Third, asymmetric complexity refers to causal asymmetry and asymmetric relationships. Causal asymmetry means that combinations are associated with a variable, but the opposite of that combination is not related to the absence of the variable. For example, even though users scoring high on neuroticism and agreeableness are at risk of perceiving technostress, this does not imply that users low on neuroticism and agreeableness are at low risk of perceiving technostress. Asymmetric relationships refer to situations where one specific variable can be associated with another variable with a high *and* low level. For example, research has revealed that neuroticism is associated with a high *and* a low risk of perceiving technostress, as it depends on other personality traits (Pflügner et al., 2021). Clearly, taking a configurational perspective allows cross-sectional data to be used to provide insights into different types of causality beyond cause-effect relationships.

The final recommendation is to conduct cross-sectional studies as **part of mixed- or multi-methods research**. Combining different research methods (e.g., qualitative, quantitative) or conducting multiple studies offers many advantages (Venkatesh et al., 2013), including overcoming the limitations of cross-sectional studies. Among others, Venkatesh et al. (2019) collected qualitative and quantitative data. While they mentioned their cross-sectional data does not permit drawing causal inferences, their qualitative data initially confirm the sequence of the relationships. A similar argumentation is provided by Zhang (2017) when suggesting that the quantitative part points to the direction and strength of relationships, while the qualitative part reveals why those relationships exist. As shown by Liang et al. (2019), additional research designs can also be integrated (e.g., experiment) to address the limitations of cross-sectional studies. Mixed- or multi-method research designs might overcome the limitations of cross-sectional data if authors were to complement a cross-sectional Study 1 design with a Study 2, which uses longitudinal, experimental, or qualitative data. In such a research design, the meta-inferences deduced via both studies (Reis et al., 2022) are a tool to provide valuable theoretical insights that reveal associations between variables (from Study 1) and cause-effect relationships (from Study 2).

5. Elusive causality and cross-sectional data

While causality is difficult to establish in purely cross-sectional studies, this does not imply these studies cannot contribute to *making*

a case for causality. As mentioned above, causality requires temporal precedence, covariation, and control of third variables. While the first condition is not met, covariation can easily be established. Similarly, using covariates in multivariate analysis can control for third-variable effects. Even path modeling techniques, like SEM, offer structural controls through the model fit that can engender some confidence in causality. Further, strong causal logic that describes the (theoretical) mechanisms behind the relationships is a powerful way to argue for causality.

Given the massive proliferation of digital technologies in modern life, causality between these technologies and social constructs is becoming increasingly elusive. These newer technologies are "embedded" in the social context and have "agency", thereby exhibiting two-way causal relationships with the context (Grover et al., 2020).

6. Concluding remarks

Many IS research papers use cross-sectional designs to gather data. While cross-sectional design's benefits can explain its frequent use (e.g., inexpensive, efficient data collection), it has significant shortcomings, including, among others, the difficulty of deriving cause-effect relationships, the non-existence of a temporal order between the collected variables, and the limited ability to test temporal causality. To realize the benefits of cross-sectional design, we recommend that researchers consider the research questions, the method, and the data when evaluating the fit of cross-sectional data with their research objective. We offer several recommendations for best practices in using cross-sectional data (e.g., as part of mixed-method studies or following configurational perspectives) to help scholars align their method with their data appropriately, and thus make more viable and compelling theoretical and practical contributions.

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