EDITOR'S COMMENTS

Proactively Attending to Uncertainty in IS Research

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The IS field has been seeing a significant change in its research practices arising from novelty in the focus of the work and how research is conducted. Pick up an issue of an IS journal or attend an IS conference or workshop, the headlines are very likely to mention novel data, novel methods, and novel contexts as differentiating aspects of the work.

Alongside the pursuit of novelty, we have seen an accompanying narrative about the need across disciplines to introspect on research practices and address issues challenging the robustness of results and the accretion of knowledge toward a cumulative tradition. There have been reports spanning diverse fields of study ranging from medicine to psychology to artificial intelligence on the challenges in replicating results. This has prompted scholars to revisit thresholds for statistical tests, for example, smaller Type 1 error rates for "new discoveries" as research in novel settings may be more subject to variation in procedures and higher uncertainty (Rigdon et al. 2020). The limitations of null hypotheses statistical testing and the utility of incorporating a range of metrics (e.g., confidence intervals, effect sizes, power) have been broadly discussed. They have also triggered assessments of reporting practices and proposals for guidelines for information systems scholarship (Mertens and Recker 2019).

While limiting uncertainty in the research by imposing constraints or raising thresholds for criteria is important, it is "only quantifying and managing uncertainty proactively" that will enable us to systematically advance our research practices over time (Rigdon et al. 2020). This proactive stance requires understanding the sources, types, and extent of uncertainty in a study. As a researcher pursues novelty in methods and domains of inquiry, the research is likely to be subject to new sources and types of uncertainty, some of which may be estimated by statistical approaches while others may require subjective assessment. Regardless of the assessment approach, a holistic stance to uncertainty in the research requires consideration of the link between the pursuit of novelty and the accompanying uncertainty so the researcher can better attend to uncertainty in a study.

In this editorial, I discuss the uncertainty in IS research that stems from three key sources of novelty: the data-generation processes, methods, and contexts (see Table 1). Understanding the underlying types of uncertainty from these sources is a first step to managing them effectively.

Uncertainty Arising from Novel Data-Generation Processes

IS researchers in recent years have been creatively leveraging the increasing availability of granular digital traces in organic settings and in hybrid organic and designed settings to take on new problems, apply a new lens to old problems, and conceive novel research designs (Rai 2016).[1] These digital traces are being generated by technologies such as internet-of-thing (IoT) devices, digital platforms, and social media. These data are attractive to researchers as they provide access not only to a large number of observations but also enable the construction of a high-dimensional representation of observations by identifying attributes from structured and unstructured data. Researchers are employing automated protocols to extract such data from digital platforms and develop representations of states and events over space and time, alongside hyper-contextual attributes that characterize social structure, individual characteristics, and so on.

[1] *Organic data* refers to data not collected following an explicit research design but represent natural "digital footprints" of activities (Groves 2011). Such data may be captured from various sources such as sensors, apps, or platforms. When researchers collect the data by conducting experiments on online platforms (e.g., Facebook), the boundaries between organic data collection and designed data collection are blurred as the data are likely to be generated through a combination of the experimental manipulations and the data generation mechanisms underlying the organic setting (Karahanna et al. 2018; Xu et al. 2019).

Table 1. Assessing Uncertainty from Novelty in the Research Process

Novelty	*Type of Uncertainty*	*Assessment of the Uncertainty*
Data-Generation Process	Algorithm opacity	Are the algorithms and models underlying the digital platform secretive? If yes, does it make it difficult to validly analyze and compare data over time and for replication studies?
	Signal manipulation	Are there strong incentives for stakeholders to manipulate the signals from the digital platform? If yes, does it compromise the data for the research?
	Agent ambiguity	Is there ambiguity in discerning whether an activity or motive is associated with a human or machine agent such as a bot or AI agent? If yes, does it create uncertainty on the underlying data-generation process?
Methods	Performative	To what extent does the level of maturity of the method create uncertainty in the robustness, portability, scalability, and relative performance of the method?
	Protocol	What is the uncertainty in protocols to *source*, *curate*, and *analyze* data?
	Interpretive	What is the uncertainty in interpreting the quantitative metrics on model accuracy and bias? What is the level of uncertainty in how human judgement on model validity is applied along with the quantitative metrics?
Context	Assumption	Do explicit and implicit assumptions underlying theories and models hold in the context?
	Definitional	Are construct meaning, reliability and validity of measures, as well as the adequacy of constructs in describing the phenomenon challenged in the context?
	Mechanism	Are the mechanisms—generative, causal, contingency, or other—associated with a phenomenon valid in the context?
	Evaluation	Are the procedures to evaluate the utility of theories, models, or solutions valid in the context?

However, the underlying data-generation process with these sources is typically not in the control of the researcher and may be hard to discern for the following reasons:

Algorithm opacity: Data generated on digital platforms such as Amazon, Google, Facebook, and Twitter are likely to be affected by the changes to the business models of the firms as well as the underlying algorithms and technologies that are incorporated to improve operations and services to customers. Some of these changes are likely to be secretive for competitive reasons, which can make it difficult for researchers to validly analyze and compare data over time and for replication studies.

Signal manipulation: With signals from digital platforms now playing a critical role in influencing public opinion and highly consequential outcomes ranging from elections to market value, the incentives for certain stakeholders to manipulate these signals is high. We are seeing an expanding array of adversarial tactics ranging from fake identities to use of bots to fluid identities to manipulate these signals. Platforms are responding with solutions to prevent, detect, and correct for such manipulation, but potential distortion of signals can raise uncertainty about the validity of the data for a phenomenon of study.[2]

Agent ambiguity: With the rapid deployment of machine agents such as bots and AI agents in digital infrastructures, it can be important to discern whether an activity or motive that is of investigative interest is associated with a human or machine agent (Salge and Karahanna 2018). An added consideration is that AI agents can exhibit fluid identities (Parkes and Wellman 2015). As such, agent ambiguity can inject uncertainty into the nature of the underlying data-generation process.

In sum, while there is increased sensitivity to the limitations of analyzing extremely large organic samples with statistical methods developed for small-sample populations (e.g., Lin et al. 2013), it is important that IS scholars attend to the new types of uncertainty stemming from the incorporation of novel data-generation processes into the repertoire of the field's research practices.

[2]Lazer et al. (2014) refer to "blue team" dynamics as the influence of the self-interest of the platform owner affecting the data streams and "red team" dynamics as the influence of the self-interests of platform-service users and parties affecting the data streams.

Uncertainty Arising from Novel Methods

New research methods can have a significant impact on IS scholarship. They can position scholars in a community to employ fresh approaches to take on enduring problems and those previously seen as largely intractable, and can offer researchers with significant competitive advantages in the discovery process. As novel methods are introduced, we inject uncertainty into the research process as discussed next.

Performative uncertainty: Insights on robustness, portability, scalability, and relative performance of novel methods emerge through evaluation and use in diverse application contexts. These insights provide critical feedback for the refinement and maturation of methods, wherein there is a reduction in uncertainty about their performance in given problem domains and research designs.

As such, the level of maturity of the method needs to be understood in assessing the uncertainty created by the use of the methods for given research objectives and research designs.

Protocol uncertainty: New methods introduce uncertainty in the protocols that need to be followed to source, curate, and analyze data.

Consider the application of unsupervised computational methods such as Topic Modeling, Word2Vec, and Global Vectors for Word Representation (GloVe) to uncover the latent structure of textual corpora rather than imposing pre-established categories, whereby researchers need to make decisions pertaining to the following:

Sourcing the data: This is likely to involve decisions on the language, authoring, and document sources to be included as well as the procedures to collect the data.

Curating the data: This involves making choices on disassembling, trimming, and transforming the textual data; safeguarding against leaking protected data into the modeling process; and managing the data through its lifecycle from creation to transformation to use to archiving.

Analyzing the data: This process entails decisions on selecting, configuring, and executing algorithms; for example, assessing the correspondence of an algorithm's assumptions to the data, setting parameters (e.g., number of topics, number of clusters) of the algorithm, and choices on writing, modifying, and executing the code.

While a substantial body of work on the application of these techniques has rapidly developed in IS, management, and business (e.g., Hannigan et al. 2019; Shi et al. 2016; Wang et al. 2018), there can be significant variance in researchers' choices, the implications of which continue to be explored and understood.

As another example, we are seeing rapid advances in deep learning methods to process image data and video data, with recent application of these methods in IS research (e.g., Liu et al. (2020) apply deep learning methods to analyze video data sourced and curated from YouTube in a chronic disease context). Understanding is emerging on the implications of the choices to source and curate data, and to select and parameterize algorithms to analyze image and video data. For instance, while researchers have a wide range of alternatives available (e.g., crowdsourcing, outsourcing, synthetic labeling, scripting) to label features in images and videos, these choices may vary in accuracy for different labeling tasks, which is consequential as small shifts in labeling accuracy can significantly bias predictive models.

In sum, researchers need to assess the uncertainty in the research process from the lack of standard protocols to source, curate, and analyze data, and design and describe the research protocols accordingly.

Interpretive uncertainty: New methods typically require a new set of considerations on interpreting the quality of the solutions. These considerations are worked out through the use of the methods in the context of the type of research problems and questions that are investigated and the research methods that are employed.

Consider the progression in machine learning methods. For supervised learning methods, validation involves using held-out samples to assess the skill of the model on unseen data. Guidelines for k-fold cross-validation have been developed over time and are employed to safeguard against data leakage (over-fitting models to the training data based on unique features that would not be available elsewhere) and to effectively evaluate models.

For unsupervised learning methods, assessing the quality of solutions involves substantial interpretive uncertainty: the criteria are more varied and less definitive, and require researchers to reconcile quantitative metrics on model accuracy and bias with human judgement on model validity (DiMaggio 2015).

As an example, researchers are likely to encounter significant interpretive uncertainty in rendering topics for textual corpora representing the discourse of political issues. The researchers may start the topic-rendering process with interpretive methods that are well honed in the humanities and juxtapose these assessments with statistical validation on expectations for prevalence of topics among stakeholders and temporal patterns of topics (DiMaggio et al. 2013). Through such a process, scholars can attempt to "locate the optimal balance between the two logics of accuracy and validity to identify the 'best' topic model to be used in further theorizing" (Hannigan et al. 2020, p. 594).

As such, understanding the nature of interpretive uncertainty accompanying a novel method is a critical consideration in assessing the comparative advantages of the new methods and how the uncertainty can be effectively managed.

Uncertainty Arising from Novel Contexts

Information technology is being developed and deployed at scale to design new realities and transform existing practices across highly varied contexts, which differ in the problem domain, values and interests of stakeholders, the technological and human agents involved in the system, as well as time and space. While phenomena may function in highly similar ways in some contexts, they may also function in highly dissimilar ways in others. From an uncertainty lens, a novel context can create uncertainty with respect to the following:

Assumption uncertainty: The explicit and implicit assumptions which underlie theories and models may be challenged as contexts change. Assumptions on values and beliefs of stakeholders, agency, interdependency, privacy norms, and risk tolerance, among others, may be challenged with a move from one context to another.

Definitional uncertainty: The meaning of a concept or construct may dramatically alter across contexts. Project control in the open source development context has a very different meaning than in traditional insourced or outsourced software development contexts, and so does the nature of contribution by developers. As IT is used to create new contexts and transform traditional ones, the stability of construct meaning, the validity and reliability of measures, as well as the adequacy of constructs in describing the phenomenon can be severely challenged.

Mechanism uncertainty: The mechanisms—generative, causal, contingency, or other—which underlie phenomena can be very different across contexts. A large-scale collective context which is altered with the incorporation of AI agents can alter the meaning of interdependence. It can also alter the generative mechanisms for the development of collective behaviors as well as the causal influence of the collective's compositional attributes on outcomes at the collective and agent levels.

Evaluation uncertainty: Contextual differences may create uncertainty regarding whether procedures to evaluate the utility of theories, models, or solutions are valid in a new context.

By proactively thinking through the uncertainty in different aspects of the research process that can arise from a novel context, a researcher can holistically manage uncertainty from the context.

Concluding Remarks

Effectively handling uncertainty in research is pivotal to the quality and utility of the knowledge that is produced by the IS field. While imposing constraints and raising statistical thresholds can be effective in restricting uncertainty, it is important to take a proactive and holistic approach to manage uncertainty that stems from the pursuit of novelty in research. Such an approach accommodates the dual pursuit of incorporating novelty in the research process *while* managing the overall uncertainty in the research.

Novelty from different sources—data-generation processes to methods to contexts—is creating dramatic opportunities to make contributions but is also introducing new types of uncertainty. While some of these types of uncertainty can be estimated statistically, the others are likely to require subjective assessment that may be guided by prior studies, reference values, experience of researchers, and judgment of experts.[3] Such an assessment can enable a researcher to assess and make transparent the "uncertainty budget" underlying the work and to reflect on the confidence that should be placed in the conclusions. Approaching the treatment of uncertainty in this manner will promote a culture of deliberately and reflectively incorporating novelty in the research process, and check against incorporating novelty for novelty's sake. It will also aid in the timely development of standard operating procedures and reporting guidelines to effectively leverage the novel approaches.

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[3]The field of metrology (measurement science in fields such as physical sciences, engineering, and legal forensics) differentiates between two approaches to quantifying uncertainty: *Type A*, which employs statistical estimations, and *Type B*, which is inherently subjective and guided by prior data, reference values, individual experience, or scientific judgment (discussed in Rigdon et al. 2020).

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Announcement of Retiring and Incoming Editors

I would like to thank the following individuals who completed their terms on the editorial board in December 2019 for their valuable service:

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