**ABSTRACT:**

Consumer questionnaires often contain a large number of questions. The questionnaire length can help ensure the breadth and robustness of collected information. At the same time, longer questionnaires cost more to field, can lead to increased dropout and less valid responses, and may be impractical because of length restrictions imposed by survey platforms and consumers’ patience. An attractive solution to this problem is an optimal question ranking that ensures the minimal possible loss of information when the survey is cut short at an arbitrary point. We propose a novel self-supervised deep reinforcement learning approach to question ranking. Our approach outperforms benchmark question ranking algorithms across multiple representative consumer data sets and is competitive against unordered column subset selection algorithms. Using our approach, we find that typical consumer data sets are redundant and can be reconstructed well based on relatively small select subsets of their columns. The reconstruction quality grows logarithmically in the relative size of the column subset, implying diminishing returns on measurement. Asking fewer questions can reduce research costs with minimal information loss and can enable previously impossible multi-scale omnibus studies. The revelatory potential of a small set of select questions poses a yet underappreciated threat to consumer privacy.