important that we continue to effectively balance the practical needs of market demands and technology evolution with the theory-driven orientation of our field. In this manner, published research and theory support continued evolution and improvement but rarely can lead the way. Although we may take a pessimistic view of the value added by theoretical advancements to early-stage innovation, we greatly appreciate efforts to move forward thinking on this important topic. Many firms in the pre-hire space are coming from fields other than I-O psychology, and we believe that our theories, research, and desire to more deeply understand the data position our field to create quality assessments that help organizations better leverage their human capital.

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Integrating Technology Into Models of Response Behavior

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Morelli, Potosky, Arthur, and Tippins (2017) are correct in calling for more conceptual models explicitly linking technology to industrial-organizational (I-O) psychology. As these authors note, in the absence of models and theories of technology to guide the research and practice of I-O psychology, the field runs the risk of chasing the impacts of specific technological

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innovations and devices rather than guiding organizations on best practices regarding the use of technology. Building theories and models that directly involve technology and placing them within individual psychological and larger organizational processes provides researchers with a way to stay ahead of the fast pace of technological innovation and anticipate its effects on measurement and prediction. Moreover, there are aspects to the use of technology that I-O psychologists are uniquely qualified to consider, including legal considerations (e.g., accessibility concerns), ethical questions (e.g., access in disadvantaged communities), practical concerns (e.g., user and target reactions), and measurement issues (e.g., construct irrelevant variance). In this commentary, we present two main points of consideration that demonstrate how I-O psychologists might use and create technology to improve assessment. First, we argue that technology can improve the measurement of psychological variables if we critically consider how technology can positively influence various parts of response behavior. Additionally, we encourage future research to consider the effects of technology in I-O psychology more comprehensively by extending the emphasis on psychological processes beyond cognition and behavior to include affect and motivation.

A Model of Response Behavior

The argument that technology can improve measurement is not new. The primary focus of the research has, as Morelli et al. (2017) note, been a reactive one in which "the primary concern with using a new assessment medium is that the technology introduces error" (p. 638) in measurement, which is subsequently investigated using tests of measurement invariance. The focal article authors argue that conceptual models of how technology interacts with the test taker, the test itself, the testing environment, or all three (i.e., the four questions on p. 639) can help preemptively answer questions regarding from where measurement error results. By integrating components of technology into existing models of response behavior, researchers and practitioners can leverage technological innovations to *a priori* minimize measurement errors. Furthermore, by linking technological design features to the various parts of the response process, I-O psychologists can actually help develop technological innovations with specific goals in mind rather than simply taking advantage of what others have developed.

Figure 1 presents a model of the cognitive processes that underlie responding to a survey item (Sudman, Bradburn, & Schwarz, 1996). Although Sudman et al. (1996) presented this model with respect to survey items, it is readily applicable to any question format insofar as the steps outlined in Figure 1 are necessary for responding to any question posed.

The first step in responding to a question is accurately interpreting the question. Measurement can be adversely impacted if the questions asked to

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Figure 1. Sudman, Bradburn, and Schwarz's (1996) model of survey responding.

respondents are not interpreted the same way because of wording differences or differences in the way the question was understood (Schwarz, 1999). Technology can influence how test takers interpret questions. Research on training design in the cognitive and educational psychology literatures suggests that design efforts to highlight critical information and reduce extraneous information will enhance recognition and rehearsal of important points (Mayer, 2008). As Arthur's (2009) model suggests, technology has the potential to increase cognitive load, which could subsequently lead to overwhelming individuals' attentional capacities (Randall, Oswald, & Beier, 2014), making it less likely that test takers will detect detail and comprehend questions adequately. Thus, to facilitate question interpretation, technology could direct attention to important instructions and item components without distracting individuals and muddling comprehension with irrelevant, distracting features.

After interpreting the question, respondents have to retrieve information from memory to provide an answer to the question. Measurement can be adversely impacted if respondents' retrieval of information is limited or selective therein responding to the question without fully considering all aspects of what was asked, such as when supervisors make performance ratings based on whatever they can recall about an employee's performance at the time he/she fills out a performance evaluation (e.g., Borman, 1978). With the assistance of technology at the first stage, mental effort can be conserved that will assist with information retrieval. Furthermore, technologies that utilize multiple media methods (e.g., pairing text with visuals), and those that provide job-relevant contextual cues and examples can facilitate the cognitive processes of rehearsal and retrieval (Mayer, 2008; Salas & Cannon-Bowers, 2001). Therefore, technology that does not overburden attentional capacity and that uses rich, relevant media should facilitate information retrieval.

After retrieving the information, the respondent must engage in a judgment process wherein he/she evaluates the retrieved information to provide an initial answer to the posed question. Measurement issues can arise from forming a judgment from selectively recalled information. For example, the aforementioned supervisor's recollection of an employee's performance may be downwardly biased given that negative information can loom larger than positive information (Skowronski & Carlston, 1989). This negative bias can

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result in improperly weighting information when forming a judgment. Cognitive feedback can improve performance judgments by making decision makers aware of how they are utilizing the information at their disposal (see Balzer, Doherty, & O'Connor, 1989). Measurement error stemming from the judgment process could be mitigated with technology that facilitates real-time cognitive feedback.

After forming this initial judgment, the response has to be formatted to fit the type of response requested. Measurement differences occur with different response formats (Schwarz, 1999). To continue the performance rating example, forced ranking scales require a different response formatting than absolute rating scales, which can impact greatly the overall measurement of performance (Goffin, Gellatly, Paunonen, Jackson, & Meyer, 1996). In personnel selection, different response formats (e.g., self-report, performance-based) also introduce different sources of error (e.g., faking vs. cheating, retest contamination; Lievens, Reeve, & Heggestad, 2007; Villado, Randall, & Zimmer, 2017). Technological advances that allow for a more direct mapping of judgments to response options could mitigate errors arising from this stage of responding. The computer adaptive rating scales (CARS; Borman et al., 2001) are one example of leveraging technology (i.e., computer adaptive testing) with scale development (i.e., ratee-targeted behavioral statements) to help respondents map judgments onto responses and minimize measurement error.

Finally, before submitting their response, respondents have the opportunity to edit their initial responses. These edits can be active attempts to present a more positive image (e.g., Dalal & Hakel, 2016) and faking in personnel selection (e.g., Griffith, Lee, Peterson, & Zickar, 2011). Importantly, response editing can be expected for even non-self-report scales, such as when performance raters might allow political considerations to cloud their ratings (Levy & Williams, 2004). The issues with respect to measurement quality in this last stage are evident: Actively misrepresenting one's standing on a construct limits the validity of the measurement. The use of technology may mitigate these intentional distortions. We might expect, for example, that the display of information, or *transparency* features, as highlighted in Potosky's (2008) framework, might influence response editing. High structural transparency, wherein it is easy for test takers to review multiple answers at one time, might lead to different editing patterns appearing more consistent or desirable than if the technology design was low in transparency, making it is more difficult for test takers to review many items at once. Thus, to the extent that technology enables test takers to review past answers or multiple answers at once, we might expect to see more response distortion and measurement error.

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Moving Beyond Cognition and Behavior

Theory and research must incorporate both affective and motivational processes in addition to cognition and behavior in order to capture additional potential sources of measurement error due to technology. Ignoring how affect and motivation influence and are influenced by technology would leave models and theories of technology and I-O psychology incomplete. Focusing exclusively on cognitive and behavioral aspects of technology misses other crucial processes.

Our review of the Morelli et al. (2017) focal article, and admittedly our own treatment of technology design in stages of response behavior, tended to emphasize the cognitive and behavioral aspects underlying human behavior at the expense of the role of affective and motivational pathways. For example, Arthur, Doverspike, Kinney, and O'Connell's (2017) structural characteristics and information processing model focuses on cognitive traits and processes that predict cognitive load; likewise, Sudman et al.'s (1996) model in Figure 1 also focuses on the cognitive underpinnings of respondent behavior. However, we also know that affect and motivation are important considerations in the measurement process. For example, affective reactions and emotions experienced during the application process and test taking produce applicant reactions that can influence job choice, psychological contracts, and broader perceptions of organizational justice and commitment (e.g., Brief & Weiss, 2002; Hausknecht, Day, & Thomas, 2004; Morrison & Robinson, 1997). Moreover, test-taker motivation can interact with cognition to predict applicant performance based on features such as reward valence, expectancy, and task difficulty (e.g., Kanfer & Ackerman, 1989). Thus, motivation has the potential to influence test performance by introducing construct-irrelevant variance when it leads to increased effort, persistence, preparation, or even unethical behaviors like cheating or faking (Randall & Villado, 2017).

Therefore, future research that incorporates technology directly into theoretical models should account for the effects of technology on behavior, not just through cognitive and behavioral pathways, but through affect and motivation as well. The third technology perspective that Morelli et al. (2017) highlight—sociomateriality—allows for the incorporation of motivation and affect as part of the purpose and typical use of technological tools utilized for selection, and may be a good area to investigate some of the interactive effects of these pathways to behavior on measurement error. Drawing from research in e-learning, affective reactions and engagement become increasingly important predictors of success in technology-enabled environments (Brown, 2005; Sitzmann, Brown, Casper, Ely, & Zimmerman, 2008), so these pathways may similarly be more deserving of emphasis in technology-based assessment. Test takers need to interact successfully with the technology

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platform in order to persist and complete the assessment, hopefully with minimal contamination from interfering emotions (e.g., frustration, anger) and motives (e.g., low tech self-efficacy, boredom). Indeed, similar arguments have been made with respect to candidate experience as part of the recruitment and selection process (e.g., Schmit & Ryan, 1997). Thus, future research should more directly acknowledge how technology design and use can impact not only cognition and behaviors, but also emotional and motivational routes to behavior throughout the selection process. Similar to the considerations for the behavioral response model we addressed previously, acknowledging the impact of technological tools and design choices on affective reactions and motivational processes will inform technology use and implementation.

Conclusions

Morelli et al. (2017) highlighted the importance of models and theories that directly integrate technology into I-O psychology. The purpose of this commentary was to provide readers with an example of how researchers and practitioners can proactively consider technology solutions as ways to minimize errors in measures stemming from cognitive, behavioral, affective, and motivational sources. Rather than explore whether or not technology adversely impacts measurement (i.e., construct irrelevant variance), we propose that researchers and practitioners can explore how technology can mitigate measurement error in ways that have not heretofore been considered.

Although our commentary focuses on examples from employee selection and performance appraisal, our ideas are readily extendable to areas outside of selection and assessment, including leadership, teams, motivation, and performance management, among others. Explicitly integrating technology with the existing theories and models of an area of I-O psychology is perhaps more common in the more technology-dependent areas of I-O psychology, such as training, but as electronic human resource management (eHRM) changes the way HR functions are performed, this work will be increasingly important. For example, researchers in the domain of e-learning (Johnson & Randall, in press; Stone, Deadrick, Lukaszewski, & Johnson, 2015) have drawn insights for training design, delivery, and evaluation from technology-based theories, including those from the management information systems literature such as task–technology fit (Goodhue & Thompson, 1995), media synchronicity theory (Dennis, Fuller, & Valacich, 2008), and technology acceptance model (Davis, Bagozzi, & Warshaw, 1989). Thus, as Morelli et al.'s (2017) focal article indicates, more deliberate integration of technology-based theories from related

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fields into other areas of I-O psychology will require a multidisciplinary focus.

In sum, we hope that our commentary adds to Morelli et al.'s (2017) call to integrate technology directly into models and theories of I-O psychology by encouraging researchers and practitioners to consider how technology can improve the measurement of psychological variables. Such an effort will require a multidisciplinary focus and include all levels of psychological processes (cognitive, affective, motivational, behavioral) but will utlimately improve theory and measurement, and will promote a more active role for I-O psychologists in technological innovation and design.

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The Big, Gig Picture: We Can't Assume the Same Constructs Matter

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I am concerned about industrial and organizational (I-O) psychology's relevance to the gig economy, defined here as the broad trends toward

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