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The Work of Educational Psychologists in a Digitally Networked World

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New digital technologies have had a dramatic effect on all arenas of human work, and the work of educational psychologists is no exception. There are many ways in which we can think about the role that technologies play in what we do as scholars and researchers of educational psychology. Technology, for instance, has changed how we think about teaching and learning in two key ways. First, it has influenced the kinds of models and theories we have of the mind (from clay tablets to digital computers). Second, technology has changed the ecology or contexts within which learning occurs to include several intersecting spaces (temporal, spatial, home, community, online, etc.).

A close examination of the relationship between technology and the work of educational psychologists reveals changes in nearly every aspect of the work that educational psychologists do. Thus, we have organized this chapter according to the role that technology has played in the everyday activities of educational psychologists, grouped into eight general categories, briefly described below.

1. **Study phenomena.** Educational psychologists study phenomena and contexts where teaching and learning occur. New technologies provide new phenomena and contexts for teaching and learning through the advent of social media, games, and virtual learning environments. These new learning environments also provide new kinds of data and new techniques for data analysis.
2. **Design studies.** Technology affords new forms of research designs allowing, for example, researchers to track individual behavior through online environments, provide tailor-made inputs to individual students (or groups of students), and develop new models of simulation and modeling of virtual learners.
3. **Collect data.** New technologies have afforded new types of data to researchers (including data from educational neuroscience, simulated data, eye-tracking data, video data, and social network data), leading to changes in data collection.
4. **Assess learning.** Digital technologies offer new possibilities and opportunities for assessment of learning through the design of new assessment tasks and the power of large-scale assessment through automated scoring, immediate reporting, and improved feedback.
5. **Analyze data.** New technologies lead to new forms of data analysis—offering tools that provide greater power and efficiency in how quantitative and qualitative analyses are conducted.
6. **Develop theories.** The development of sound, predictable, data-driven theories is paramount to the conduct of research in educational psychology. Some of the consequences of the inclusion of digital technologies are design-based research, testing boundary conditions for the application of theories, and questioning the value of theory itself.
7. **Read, write, publish, and disseminate ideas.** Today's educational psychologists must consider how new technologies have contributed to changes in publishing, accessibility, and scholarship.
8. **Confront ethical issues.** As in all research, new technologies have brought about a new range of ethical issues that educational psychologists have to contend with (such as those related to data security and new regulations concerning institutional review).

We explore the changes occurring at the intersection of educational psychology and technology in the sections below, which correspond with the eight general categories of activity of educational psychologists. Some of these categories are more specific to the work of educational psychology scholars than others. For instance, under "Study phenomena," we explore phenomena now available for investigation by educational psychologists due to technological change, but, under "Read, write, publish, and disseminate ideas," the changes we discuss apply more generally to scholars in many, if not all, disciplines. That said, we focus attention on issues specifically impacting the work of educational psychology researchers, paying less attention to issues that have broader implications across all fields of study. We limit our

discussion of the collaborative work educational psychologists do facilitated by technological tools, and refrain from discussing new technology-based sources of data such as electroencephalograms (EEGs), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET) scans in the burgeoning subfield of educational neuroscience. Although these are valuable for educational psychology research, we have not addressed these issues in the present chapter for reasons of space as well as the fact that these topics are addressed in other chapters in this handbook (see Chapters 5, 25, and 26 in this volume).

Study Phenomena

New technologies have significantly impacted the phenomena we study as researchers in two primary ways. First, technology has introduced a host of new phenomena worthy of research through the advent of social media, games, and virtual learning environments. Second, it has shifted traditional dichotomies, such as informal versus formal, and created new ones, such as virtual versus physical and online versus offline. By introducing new phenomena, technology has often shifted the landscape of these "boundaries," thus complicating what on the surface may appear to be somewhat simplistic dichotomies.

Social Networks

Technological advancements have contributed increasingly to people's adoption of *social media*, a term often used to refer to online technologies and applications which promote people, their interconnections, and user-generated content (Cormode & Krishnamurthy, 2008). Among the many different kinds of social media, of particular interest to educational psychologists are *social network sites*, including Facebook, LinkedIn, Google Plus, and Twitter, which are dominant in the early decades of the twenty-first century. Such social network sites typically feature the ability to consume, produce, or interact with streams of user-generated content provided by one's connections (Ellison & boyd, 2013).

Social networks offer educational psychologists the opportunity to study a wide range of empirical questions such as how these networks factor into, shape, and are shaped by the learning ecology of their participants (Barron, 2006). Social networks are increasingly being used in virtually all areas of pedagogy (Manca & Ranieri, 2013; Ranieri, Manca, & Fini, 2012). For instance, scholars have studied how online social networking can facilitate new forms of collaboration not feasible with traditional communication technologies (Greenhow & Li, 2013) and the use of social media for teachers' professional development (Ranieri, Manca, & Fini, 2012). This work suggests possibilities for educational designs powered by social media within a variety of learning and teaching contexts as well as a revisiting of conventional learning theories as they play out in such contexts. For instance, in studying social networks, scholars have found that social links indicated in automatically generated and dynamically updated network graphs (e.g., Facebook visualizations) are not valid indicators of real user connection as previous research using social graphs from physical observations of in-person interactions would suggest (Wilson, Sala, Puttaswamy, & Zhao, 2012). Other scholars have examined how aspects of computer-supported collaborative learning theory, generated in other collaborative spaces, are contradicted in social network sites (Judele, Tsovaltzi, Puhl, & Weinberger, 2014). Such studies suggest how educational psychology research may shift, requiring more accurate modeling to evaluate social network phenomena in light of new technologies (see Chapter 25 in this volume).

Games

Although the educational possibilities of learning from games have been conjectured and studied throughout history, the advent of digital games is a relatively recent phenomenon with tremendous economic, cultural, and social implications (Squire, 2006). Educational psychologists have studied the cognitive, social, and emotional impacts (both positive and negative) of game playing under various conditions. On the positive side, research has shown playing computer games can enhance cognitive processes such as perception, attention, and cognition (Anderson & Bavelier, 2011); reaction time (Karle, Watter, & Shedden, 2010); and mental rotation (Sims & Mayer, 2002). Games have also been shown to have some success in transferring learners' skills to "real-world" situations, including flight training, the training of surgeons, the care of diabetes, and the development of prosocial behavior (Tobias, Fletcher, & Wind, 2014). On the other end of the spectrum are concerns that game play is often associated with lower school achievement (Gentile, 2011) and negative behaviors such as aggression (Tobias et al., 2014).

The important issue for educational psychologists is that these game interactions can have significant psychological consequences because they occur in environments characterized by pretense, virtuality, distance, and mediation. Learning in these networked, digital spaces often occurs through active participation in the game's virtual social structures (Salen & Zimmerman, 2004) and is evaluated through actual performance—a different manner of engaging in learning than in a traditional learning environment such as the classroom.

Virtual Environments

Virtual environments are systems where individuals interact with simulated objects, people, or environments. *Virtual worlds* represent one type of virtual environment. In virtual worlds users are often identified by two- or three-dimensional representations called *avatars* and communicate with each other using text, visual gestures, and sound. Educational psychologists can explore how such environments integrate with, intensify, or contradict learning and teaching in physical environments and explore learners' negotiation of identities within and between these spaces (Tettegah & Calongne, 2009). Moreover, virtual environments form an integral component of the growing contemporary use of online education.

Online Education

Online education is fast becoming an alternative mode of teaching and learning and a supplement to traditional face-to-face education (Picciano & Seaman, 2009). Online education may consist of wholly online courses or *hybrid* or *blended* courses that combine online components with traditional face-to-face components. Most recently, online education has seen the rise of massive open online courses (MOOC), a term referring to online courses targeting large-scale interactive participation and open access via the internet. Regardless of format (wholly online, blended, or MOOC), online courses may consist of traditional course resources such as readings, videos, tools to facilitate synchronous and asynchronous participation, and course management systems.

The rise of online education offers new phenomena for educational researchers to examine. Researchers have examined issues such as the effectiveness of online instruction compared to face-to-face instruction, practices associated with effective online learning, and factors that influence the effectiveness of online learning (Means, Toyama, Murphy, Bakia, & Jones, 2010). Additionally, approaches in online education (particularly MOOCs) have the potential to generate large datasets—through both the content people upload and the behavioral traces (such as log files) they leave behind—which can be mined for patterns and used to test learning and teaching theories at a scale not previously seen.

Design Studies

In many ways, how we design studies is at the heart of what research is and of what we do as educational psychologists, academics and scholars; this issue therefore drives the central issues in each of the eight categories of work that educational psychologists do. In this section, however, we focus on three new contexts that digital and networking technologies have created for designing new studies and two important research design strategies that digital environments provide.

Studies in Virtual Worlds

One new context that networking technologies have provided is the online virtual world—digital environments where people can work and interact in a somewhat realistic manner. Research contexts include existing recreational, multi-user, virtual worlds that have been adopted for educational purposes (e.g., Active Worlds or Second Life) or worlds designed specifically for educational purposes, such as River City (Clarke, Dede, Ketelhut, & Nelson, 2006). Virtual worlds make attractive research environments because they can be designed to automatically generate data as users interact with the world (e.g., activities most performed, time on task, content generated by users). Designed studies of virtual worlds can examine how well pedagogical approaches used in other settings function in these worlds. They can also test prominent learning theories, such as theories of self-directed learning and motivation; compare learning and teaching processes and outcomes in-world and out; and explore the co-evolution (or contradiction) of learning and design (De Lucia, Francese, Passero, & Tortora, 2009). Virtual worlds designed for education can be studied in terms of how well they help learners understand disciplinary concepts (e.g., scientific reasoning: see Chapter 24 in this volume), to test theories of how people learn and teach (Bransford, Brown, & Cocking, 2000), and to explore how learning, pedagogical, and design theories co-evolve and shape one another over successive iterations of virtual-world participation and design revisions.

Simulations and Modeling as Experimentation

A second related context that can provide expanded sites for research are simulations and other forms of computer-generated modeling. *Simulations* are constructed worlds that are a close representation of the physical world governed by the same rules. Simulations and simulated labs (e.g., virtual frog dissections in science education) may be useful where repeated practice is required or where the actual physical experiment would be too costly, time consuming, or otherwise impractical to enact in real life. Simulations have been used to illustrate key principles in disciplines such as biology, chemistry, physics, and earth and space science. Studies can be designed to examine whether and how simulations help learners understand disciplinary concepts. For example, studies of the simulation environment NetLogo have investigated middle- and high-school students' derivation of the ideal gas law from microlevel interactions among gas particles in a box (Wilensky, 2003); creating and testing models of predator–prey interactions (Wilensky & Reisman, 2006); and exploring the rates and directions of chemical reactions for individual molecules (Stieff & Wilensky, 2003). Studies can also be designed to compare learners' outcomes following simulations versus hands-on lab experiences (Ma & Nickerson, 2006). As technology improves, so does the fidelity of the simulations, providing ever-greater opportunities for future research (see Chapter 20 in this volume).

Online Education and Massive Open Online Courses

The rise of online education and MOOCs targeting large-scale interactive student participation, open access via the internet, interorganizational collaboration, and the generation of big datasets provides opportunities for interdisciplinary, intercultural research on a scale not previously seen.

Though relatively new, the potential for research on MOOCs is immense. MOOCs allow for the development of learning analytics that can be used for adaptation and personalization of curriculum through predictive modeling and forecasting of learner behavior and/or achievement or for the application of social network analysis techniques to optimize learner interactions. Insights generated from such studies may contribute to new theoretical models, such as models of self- and peer-assessment, as well as to the design of automated mechanisms to support and augment students' learning goals and processes.

Designing Studies with Big Data

What is common to all of the technological contexts described above is that users leave complex traces of their interaction with the environment, the content, and with each other and thus generate large and complex datasets. By employing a combination of modern artificial intelligence, machine learning, and statistical techniques, these datasets can be examined in a variety of ways to reveal relationships, patterns, and insights not easily discoverable through standard database management tools or data-processing applications. Coinciding with the rise of big data, learning analytics is a recent area of scholarship that seeks to collect, analyze, and report data "about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Long, 2011, p. 4).

However, designing studies involving big datasets can also be problematic. Designed studies can oversimplify complex human actions and motivations, magnify data errors when multiple datasets are combined, and create divides between those who have access to big data and those who do not (boyd & Crawford, 2011). Additional challenges include establishing norms for collaborating across big data projects, creating ways to measure and reward individual contributions, and defining the most pressing problems; that is, distinguishing the needle from the big data haystack.

Studies in which Every Participant gets a Tailor-made Condition

Newer digital technologies also enable educational psychologists to design studies in which each subject is assigned a custom experimental condition. For instance, diagnostic educational gaming environments that unlock levels of game play based on how and how well individuals progress through the game can provide each subject with a tailor-made condition. Similarly, different versions of an online course that are randomly assigned to learners can allow for true experiments to test different interventions or theoretical frameworks. Such technologies suggest the promise of tailoring research conditions for individual participants.

Collect Data

With new technologies come new types of data. Changes in the available types of data also bring about changes in the focus of researchers' attention, the methods they use to study these phenomena, and the types of questions they ask. Key possibilities for new types of data afforded to educational psychologists by technological advances are highlighted in the sections that follow.

Data from the World Wide Web

Since the advent of the first widely available web browser (Mosaic) in 1993, the internet had grown to over 2.3 billion users by the year 2014. Along with the explosion in the number of users, websites, domain names, and sophisticated designs, the types of data available as tools have also dramatically increased for businesses, marketers, and, more recently, researchers.

Web analytics are the data collected automatically by web servers to track visitors' interactions and behaviors with websites. When combined with data from other websites and browser tracking (via cookies and session data), information can be generated about the visitor to a website, including the visitor's prior browsing history, likes and dislikes, sex, age, income, ethnicity, and purchasing history. Another source of data from the internet comes from a technique called *web content mining* or *web scraping* (Bharanipriya & Prasad, 2011). In this approach, data are gathered or extracted from websites via automated processes. These techniques of generating big data have the same strengths and weaknesses described above.

Simulated Data

Not all data come from direct observation of phenomena or derived measures. The rise of computing technology has driven increased use of *simulated data*, data generated by computing processes that simulate data that might be otherwise difficult to obtain. This technique has been commonly used in statistics to test the properties of many statistical procedures. For example, in simple statistical analyses such as the *t-test*, the statistical power (type II error) can be computed exactly from formulas if all statistical assumptions are met. Other procedures, like non-parametric statistical analyses, do not have easily computed type II values, because the procedure depends so heavily on the type of data to be analyzed. In these cases, *Monte Carlo techniques* (Kalos & Whitlock, 2009), a type of simulated approach, can be used to generate many samples of the kind of data expected. The statistical procedure is then run on these simulated data, repeatedly, in order to establish the rate at which the null hypothesis is rejected. This rate is an estimate of the type II error rate (for examples of this, see Mumby, 2002; Muthén & Muthén, 2002).

Given recent advances in computing power, Monte Carlo techniques will soon become more commonplace in other arenas of social science. Bakker, van Dijk, and Wicherts (2012) explored how researchers have found statistically significant results 96% of the time, when on the surface there is insufficient statistical power to support rejecting the null hypothesis at such a high rate. Generating data for multiple studies under varying effect sizes, sample sizes, and research practices (analyzing more than one variable, sequential testing, splitting studies, and removing outliers), these researchers found that true type I error rate may be as high as 0.40 using such practices and may explain why 96% of studies report significant results.

User Data Capture

Traditional methods of research in the educational sciences, such as think-aloud protocols, interviews, surveys, and observations, rely on second-hand or indirect data. Technology is increasingly providing opportunities for researchers to collect first-hand data from participants. For example, a tool like Morae allows researchers to simultaneously record screen captures, audio and video data (typically of users interacting with the system), and mouse and keyboard clicks. Morae also has built-in analyses that detect patterns in the massive amounts of data that such recordings can generate.

The challenge with data generated from seamlessly recording participants' interactions with systems is that, even when built-in analyses detect patterns in the massive amount of data captured, researchers must decipher what such patterns mean. It is one thing to know that at a particular moment in time a user clicked on a particular portion of the screen; it is another matter completely to figure out why the user did so and what that interaction means. More research is needed to help uncover patterns in the data and ascribe meaning to data.

Eye-Tracking Data

One type of user data capture, eye-tracking data, is particularly noteworthy. The previously mentioned forms of user data capture all record what participants do—where they click, what they say, and what they are doing. By recording the movements of the human eye, researchers can gain insight into what participants pay attention to, whether or not that attention is brief or extended, and what may be interesting to participants (Duchowski, 2007). For example, Galesic, Tourangeau, Couper, and Conrad (2008) used eye-tracking data to investigate possible causes for response order effects (i.e., that survey responses tend to be skewed in favor of responses presented earlier in the list of choices). They found that participants often take cognitive shortcuts. The most salient of these is that participants tend to devote more attention to earlier choices and less (sometimes none) to later choices.

The cost of procedures for eye tracking is consistently declining, increasing access of these data to researchers. This newfound access to eye-tracking data has fueled the development of new analysis tools and, in many cases, add-ons to existing data analysis tools. For example, *Morae* offers several plugins and extensions to seamlessly integrate eye-tracking data with key-logging data, allowing for researchers to synchronize participants' actions with their perceptions (Alves, Pagano, & da Silva, 2010).

Video Data

Dramatic changes in affordability, availability, storage, and quality of video have led researchers to routinely use it as research data. Tools such as Transanna, Morae, DIVER, and ATLAS have been developed to help researchers organize, code, analyze, and connect video data to other data (e.g., transcripts, interviews, qualitative analyses).

The new affordances that video data offer to researchers bring new challenges. Derry et al. (2010) identified four challenges to researchers using video data: (a) how to *select* specific elements to focus study on within complex settings or large corpuses of video; (b) choosing what analytic frameworks to guide the *analysis* of video; (c) choosing the appropriate *technology* to organize, store, and analyze the video; and (d) adhering to appropriate *ethics* involving consent and use of video data while at the same time promoting sharing and collaboration.

Data from Social Networks

Online social networks present a number of novel types of data available to researchers. These include the "network" or community itself as a representation of connections between individuals, which can be depicted as a network graph summarizing the "degrees of separation" between people in a community. Types of data available from these networks include the content of the interaction (their messages or photos) and social tagging (short descriptions or signifiers of content) that occurs (Aggarwal, 2011). Other types of data that emerge from social networks include *reputation* systems, *badge* systems, and *influence scores*. These measures capture and reward useful user behavior—such as completing a task, helping others, and so on. Clearly these "reward" structures are important to researchers in that they provide meaningful information about user behavior and interactions (see Chapter 25 in this volume).

Assess Learning

Digital technologies also offer new possibilities and opportunities for the assessment of learning, primarily through the design of new assessment tasks as well as the power of large-scale assessment through automated scoring, immediate reporting, and improved feedback. One fundamental challenge, however, faced by all assessment techniques (irrespective of the use of technology) is making the assessment tasks valid and reliable, even while making them amenable to computational analysis. For instance, computers are good at evaluating responses to tightly constrained questions, such as multiple-choice questions, and less effective when evaluating open-ended, constructed responses, such as the traditional essay. Though the nature of multiple-choice questions does not preclude the measurement of higher-order thinking skills, there is a general belief that such constrained questions typically focus on measuring lower-order skills. The demand for alternative assessments comes from both a skepticism toward multiple-choice assessments as well as the push towards more authentic, performance-based assessments (see Chapter 29, this volume).

Scalise and Gifford (2006) offered a taxonomy that may be useful in computer-based assessment consisting of 28 item types "based on 7 categories of ordering involving successively decreasing response constraints from fully selected to fully constructed," (p. 3). At the most constrained end of the spectrum are multiple-choice questions, while at the other end are assessment types that seek to measure student performance under simulated or real conditions. The five intermediate categories fall along this dimension and are classified as: (a) selection/identification; (b) reordering/

rearrangement; (c) substitution/correction; (d) completion; and (e) construction types. They also suggest that the 28 types of assessment they describe within these seven broad categories are not necessarily comprehensive in that a variety of other item formats can be designed by combining some of the types listed or through including new media formats such as video, audio, and interactive graphics (e.g. animations or simulations). Two areas (from opposite ends of the constraint spectrum) that have received significant attention are computer-adaptive testing (CAT) and automated text analysis.

Computer-adaptive Testing

CAT is the computer-based extension of the adaptive testing started with Binet in 1905 (Linacre, 2000). The term encompasses a wide range of assessment approaches administered on a computer, where the test difficulty is adaptively targeted to match the proficiency of the test taker in order to provide the best and most efficient assessment of abilities (Luecht, 2005). Behind the scenes, item response theory (IRT) is typically used to judge the relative difficulty of items, select the next items for test takers to receive, and equate items across test takers.

As CAT approaches become more commonplace, especially in the context of high-stakes testing, there are implications for educational psychologists. CAT approaches are generally considered to be more accurate assessments of skill (Thissen & Mislevy, 2000) but at the same time do not produce tests that can be strictly equated across test takers. CAT approaches offer possibilities for fast or immediate test results for test takers and can easily scale up to large participant pools. Developing the test, however, can be a time-consuming and costly endeavor as CAT approaches require the development of many more items that require large amounts of pilot data to be properly equated using IRT models.

Automated Text Analysis

Automated essay evaluation, which is derived from automated essay scoring, is the "process of evaluating and scoring written prose via computer programs" (Shermis & Burstein, 2003, p. 7). The approach uses advances in natural language processing, applied mathematics, machine learning, and computational linguistics to analyze syntax, word usage, discourse structure, and higher-level meaning such as thematic analysis. For example, latent semantic analysis (LSA) is an early approach that performed statistical computations on the similarity of all the meanings in a large text, which was then used to approximate writing coherence and the quantity and quality of the writer's knowledge (Landauer, Foltz, & Laham, 1998). More recent and sophisticated approaches include the *E-Rater* system employed by the Educational Testing Service in many of its high-stakes tests; *Coh-Metrix* (Graesser, McNamara, & Kulikowich, 2011), which provides multiple-level indices of text coherence; and *LightSIDE* (Mayfield & Rosé, 2013), which provides open-source machine learning software customizable to many different evaluation purposes. These more advanced approaches merge combinations of LSA, feature extraction (word occurrences, word dyads and triads, parts of speech), machine learning to train underlying models, and multi-level evaluation. For example, *Coh-Metrix* can generate over 100 indices (features) from a given text, which are in turn used in formulae to compute various metrics of text coherence, which some researchers have used to make direct judgments about the quality of written texts.

The growing popularity of such approaches has important implications for educational psychologists. On one hand, there are clear-cut advantages in terms of efficient data analyses that are increasingly becoming as reliable as (and less opaque than) human raters (Shermis & Burstein, 2013). On the other hand, there are legitimate concerns about an undue emphasis on product over process, a focus on the wrong qualities of writing (e.g., its function as expression), and a philosophical concern about the equivalence between how human raters and machine raters make judgments.

Analyze Data

Data in educational psychology are often used in two ways that need to be carefully delineated (Behrens & Smith, 1996). Behrens and Smith call the first level the "data of phenomena"—the recordings of sense experiences that are then transformed into a second representational level, the "data of the analysis." The data of analysis consist of records of experience, which may include field notes, survey responses, video recordings, software usage characteristics, and tally marks that count particular user behaviors. In quantitative analysis, the recording of experience emphasizes measurement and precision while qualitative analysis emphasizes interpretation. The goal in both cases is to reduce large amounts of data to representations that are comprehensible, allowing researchers to develop a deeper understanding of the original phenomena under study. Both approaches require navigating and managing a series of tradeoffs between the precision and richness of description and the validity of the inferences we can make from the data and subsequent analysis.

Quantitative Analysis

A powerful impetus for new approaches to quantitative data analysis and representation has come from the world of business and commerce, which is focused on using large datasets and user-generated data to improve decision making, managerial practices, and quality control processes. Examples include the recommendation engines of Amazon, Netflix, iTunes, Google, and Facebook, which provide users with targeted advertisements based upon past behavior.

Accordingly, it is not surprising that the use of student data for educational improvement has also seen increased prominence in education. Learners are increasingly leaving behind sophisticated and detailed traces of their actions as they work in technologically mediated environments, a form of big data then available to educational psychologists. Moreover, educational policies, such as Race to the Top and

No Child Left Behind, have added pressure to the need to collect and analyze large amounts of student data.

Technology has influenced how quantitative data analyses are conducted. At a basic level, statistical analysis packages that offer comprehensive tools for computing descriptive statistics, hypothesis testing, and drawing inferential conclusions have made statistical analyses increasingly assessable, user friendly, commonplace, and powerful. These include standard statistical analysis packages (such as SPSS, SAS, and R) as well as some more specialized packages, such as LISREL, which is used for confirmatory factor analysis and structural equation modeling.

One of the most important areas where computational power has changed educational research is in the area of data mining and visualization. *Data mining* is the process of examining large sets of data with multiple variables to uncover trends and patterns. These data-mining techniques can be combined with the capabilities of digital technologies to represent and present data in rich, visual, and intuitively recognizable formats. Standard statistical packages, such as Excel and SPSS, have increasingly powerful tools for data representation. Beyond this, there are other software programs, such as the interactive environment for data analysis and visualization MATLAB, the computational knowledge engine Wolfram Alpha, and the algebraic and symbolic mathematics package Mathematica, that specialize in the construction and display of complex and sophisticated graphical displays. As Knezek and Christensen (2014) wrote, "the distinction between analysis, modeling, and display tools is beginning to blur as 'math packages' are being routinely employed to produce elegant summaries and visual displays of findings from traditional research" (p. 219). Free web-based software applications, such as Google Fusion Tables and Many Eyes from IBM, allow researchers to upload large datasets and display the data in multiple formats, such as graphs, maps, intensity maps, timelines, and story lines.

Qualitative Data Analysis

Qualitative research has generally been defined as "any kind of research that produces findings not arrived at by means of statistical procedures or other means of quantification" (Strauss & Corbin, 1990, p. 17). Thus, qualitative researchers require technologies that assist in gathering and coding data to uncover phenomena and make meaning through analyzing patterns in stories, common ideas, and emergent themes. Organization and interpretation are important fundamentals of this work, and new technologies can assist with this (Anfara, Brown, & Mangione, 2002; Creswell, 1998). While the foundational elements of qualitative research—the guiding principles, determinants of reliability, validity, and so forth—remain in place, new technologies have shifted aspects of methodology, and in some ways have changed the way we "see" or interpret qualitative data (Brown, 2002).

Digitalized qualitative processes allow researchers to store and access a variety of types of qualitative data, including text, audio, video, and graphics files. One of the most basic and critical newer uses of technology involves the use of digital audio or video recording for field studies or interview sessions. At a surface level, such digital recordings are a way to preserve a clearer record of events and conversations, but, at another level, digital recordings afford new ways of thinking about how analysis develops out of the data and how data support it (Gibbs, Friese, & Mangabeira, 2002).

Educational researchers can now attend to small-scale and detail-oriented content in teaching and learning scenarios such as characteristics of speech, movements, or body language (see Chapter 28 in this volume). Examinations of such focused minutiae can be undertaken quickly, putting increased analytical power to work on observed data. While digital media has allowed researchers to home in on visual and audio data at a smaller scale, it has also opened up possibilities for much larger-scale studies because multiple researchers and analysts can connect and collaborate via qualitative coding software.

Computer-assisted qualitative data analysis software (CAQDAS), such as NVivo, Atlas.ti, or HyperRESEARCH, makes the core processes of organizing and coding data from observations, interviews, field research, or ethnography easier and more efficient (Lewins & Silver, 2009). By facilitating organization and categorization of data, such programs facilitate the process of meaning making (Fielding & Lee, 2002). One of the common experiences of qualitative research has always been the challenge of careful and complex management of large amounts of texts, codes, memos, field notes, and observations (Moustakas, 1994). CAQDAS options allow for greater efficiency and consistency in systematic data management.

Such software programs typically provide flexible code trees (or code books), which allow for a more sophisticated categorization and increased ease of complex data searches. A range of group codes, individual codes, and subcodes can allow new and unique visualizations of the themes within a study for a specific look at the building blocks of the study. This allows the coding process—a foundational process in qualitative work—to be not only more systematic in approaching data but also more dynamic and responsive to emergent interpretations.

As noted, many CAQDAS programs today offer coding and organizational techniques for working with video and more traditional text and/or audio transcription. Digital video has unique properties that allow researchers to capture, observe, and reobserve complex phenomena visually and then code or notate behaviors, themes, comments, or anything else of interest (Spiers, 2004). Such affordances can bring the traditional thematic organization of qualitative work to video data and allow researchers to incorporate video vignettes—another powerful addition to the story-telling tradition of qualitative research (Creswell, 1998; Patton, 2002).

Develop Theories

The development of sound, predictable, data-driven theories is paramount to the conduct of research in educational

psychology. Theories provide us with concepts, terminologies, and classification schemes to describe phenomena accurately, highlighting relevant issues and ignoring irrelevant ones. Theories also allow us to make inferences and predict the consequences of an intervention or change. Finally, theories have a pragmatic function, informing how we can apply ideas to the real world by helping us design better learning contexts and systems and by bridging the gap between description and design.

Digital technologies have changed the phenomena being studied, the kinds of data that can be collected (which ground the theory-making process), and the data analyses that are possible. Altogether, these changes in phenomena, data, and analyses have resulted in strong tests of theories not possible before. Theory generation, however, remains outside the scope of even the most intelligent computer programs. That said, technology and theory building have interacted in three significant ways. First, educational design-based research (EDBR) methodologies have allowed researchers to study the effects of technological interventions in educational settings iteratively. Second, technological contexts have provided testing grounds for the boundary conditions of psychological theories and ideas, which have typically been based on studies conducted in face-to-face conditions. Third, the rise of "big data" has potential impacts for the role of theory in educational psychology.

Educational Design-Based Research

EDBR is a type of research methodology in which educational interventions are conceptualized and then implemented iteratively in natural settings to both test the validity of existing theories and generate new theories for conceptualizing learning, instruction, design processes, and educational reform. A more detailed description of EDBR (and its variations) can be found in Chapter 2 in this volume. Our emphasis here is on two key aspects of EDBR. The first is an emphasis on the development of theory and the second is that many EDBR studies have focused on innovation driven by technology.

One of the main goals of EDBR is the development of theory—to not only use theory to provide a rationale for the intervention or to interpret findings but also help "develop a class of theories about both the process of learning and the means that are designed to support learning" (Cobb, Confrey, diSessa, Lehrer, & Schauble, 2003, p. 9). Also, though EDBR does not necessarily require the use of technology, it is frequently driven by the urge to integrate new psychological conceptions with technological possibilities. An example of EDBR and the twin emphasis on theory generation and technology-related contexts can be seen in the development of the Technological Pedagogical Content Knowledge (TPACK) framework. This framework explicates the knowledge teachers need to know in order to teach effectively with technology by extending Shulman's (1986) idea of pedagogical content knowledge to include technological knowledge (Mishra & Koehler, 2006). This framework emerged from over seven years of multiple studies aimed at understanding the development of teachers' knowledge for effective technology integration while simultaneously helping teachers (through courses, workshops, and other interventions) to develop their teaching with technology. Overall, this work led to a number of smaller studies (or EDBR "iterations") and publications that stood on their own as well as a larger framework (Mishra & Koehler, 2006) that emerged through synthesizing across the iterations.

Technological Contexts as Providing Boundary Conditions

Most long-standing psychological theories—such as theories of transfer, motivation, and mindfulness—were developed based on research conducted in traditional face-to-face situations. New technologies provide new contexts for studying human interaction and can serve as important tests of the boundary conditions under which such theories can succeed or fail. As Walther (2009) argues, "Boundaries are being foisted upon us by technological developments that may limit (or maybe revise) the scope of our extant theoretical frameworks. There are implicit boundaries that have always been there but which we have ignored, misapprehended, or failed to investigate" (p. 750). At the heart of the issue is the question of fidelity of representation or the correspondence between the virtual and the physical world and our psychological responses to these differences.

For example, consider how studies in human computer interaction show that people often treat computer respondents just as they treat humans. The computers as social actors (CASA) paradigm argues that people may unconsciously perceive interactive media as being "intentional social agents" and read personality, beliefs, and attitudes into them; more importantly, the CASA paradigm argues that people often act on these perceptions. There is a strong body of empirical evidence to support this position: People are polite to machines (Nass, Moon, & Carney, 1999), read gender and personalities into machines (Nass, Moon, & Green, 1997), are flattered by machines (Fogg & Nass, 1997), treat machines as team mates (Nass, Fogg, & Moon, 1996), and get angry and punish them (Ferdig & Mishra, 2004). Technology, however, also illustrates the boundary conditions under which such attributions fail. For instance, Mishra (2006) found that participants respond differently to praise and blame feedback from computer evaluators than they do from human evaluators, suggesting the need for a more complicated theory of interaction.

Do We Need Theories in the Age of Big Data?

The rise of "big data" has caused some to argue that theories are becoming obsolete (e.g., Anderson, 2008) and will be replaced by large amounts of data, powerful analyses, and pattern recognition. For example, Google Translate works not by "understanding" any of the texts it translates but rather by tracking patterns across a large corpus of texts in multiple languages and associating inputs with outputs. This has led some computer scientists and other researchers using big data to argue that there will be no need for theory or models of phenomena when we have enough data and patterns to process. Although this discourse has not entered the realm of education, it may soon do so. Whether or not this "data deluge" brings about the strong version of "the end of theory," educational psychologists cannot ignore the future impacts of big data on theory building.

Read, Write, Publish, and Disseminate Ideas

The processes of reading, writing, publishing, and dissemination have seen radical changes brought about by the advent of new digital and networking technologies. First, as in other academic disciplines, educational psychologists read and survey the field to conceptualize broader frames or perspectives in which to situate existing and new research. As has been explained in the scholarship on academic work life (Fry & Talja, 2007), and as touched on here, technology-driven changes in reading have an overall impact on the world of academia (Palmer & Cragin, 2008).

Reading, for example, has become increasingly on the screen (National Endowment for the Arts, 2007). This move towards more online and on-screen reading places "large demands on individuals' literacy skills" (RAND Reading Study Group, 2002, p. 4) and requires new *literacies*, *skills*, *strategies*, *dispositions*, and *social practices* (Coiro, Knobel, Lankshear, & Leu, 2008). Surveying the field, too, has been transformed by new digital and networking technologies, as new databases and citation indexes (Kousha & Thelwall, 2007; Meho & Yang, 2007) offer both qualitative and quantitative changes to how scholars access prior research and scholarship. Such tools can make it easier to gather resources from a wider range of sources and speed up the rate at which new findings can be presented and shared. This can lead to too much cognitive load but also to the creation of fresh connections to related information or to citations that would not otherwise have been possible.

Several important themes also underlie changes in the writing, dissemination, and publishing processes brought about by the advent of new digital and networking technologies. The first is the move towards *open publishing*, producing and distributing data in the "public domain" or with Creative Commons (creativecommons.org) licenses that allow public consumption and comment through open-access journals or self-publishing. More radical still are trends in how research is shared and disseminated that emphasizes *social scholarship*, sharing published or in-progress work via social media outlets. Such scholarship changes research dissemination routes, peer review, and potential audiences for work (Greenhow & Gleason, 2014; Greenhow, Robelia, & Hughes, 2009). A second influence of technology has been to change the tools available for academic collaborative writing. Today's technologies for writing can transform everything from project and bibliographic organization to the nature and process of collaborative writing. A third influence of technology has been the rise of manuscript platforms that can alter how we review and publish our work. Authors now submit their manuscripts online and can track the progress of their manuscripts throughout the review process. Because authors, reviewers, and editors record and archive information within the same online system, editors can track patterns in online activities, and these patterns can then be used to improve the journal's overall review and publishing process.

Confront Ethical Issues

Technology integration into educational psychologists' contemporary work practices raises a host of ethical issues, such as data security and human subjects issues (Moore & Ellsworth, 2014).

Data Security

In an increasingly digital and networked data environment, issues of data security have become more prominent. For example, cloud computing is frequently cited as an appealing data protection option because of many obvious affordances—ease of use, scalability, shareability, easy access to data, and built in backups. Researchers' use of cloud storage solutions, however, also raises ethical concerns associated with entrusting third-party vendors with confidential subject data (Newton, 2010).

Unknowing Participants

Technology has introduced new ways of automatically recording data about people, behaviors, and patterns of interaction that considerably impact potential participants in a research study. First, technology has introduced video recording in many facets of everyday life, including through the widespread use of security cameras, mobile device cameras, and webcams (Koeppel, 2011). Second, people's behaviors online are being recorded, both knowingly and unknowingly, through the use of session variables (e.g., "cookies"), monitoring of behavior on websites, and studies of interactions that occur online. All of this automatically recorded data has ethical implications for would-be researchers. For example, researchers studying individuals in social networking sites may inadvertently access data from individuals in their participants' network that they do not have permission to access. Many studies using data from these auto-recorded sources are determined "IRB-exempt" (see below) because the behavior is "publicly observable" and therefore does not require the consent of any participants in the research. That said, the very idea of what is (or is not) "publicly observable" in a networked, connected world is contentious and open to scholarly and legal debate.

Instructional Review Board (IRB) Issues Related to Technology

Internet-based research also raises complex issues concerning human subject protections. Topics such as confidentiality, recruitment, and informed consent become complicated when research is conducted online. For example, authentication of identity in online worlds is an issue and may inadvertently

lead to conducting research on minors or vulnerable populations. Another potential issue with internet-based research is that requesting consent should not disrupt normal group activity; however, the very act of entering online communities or chat rooms to request consent can be perceived as disruptive. Finally, even apparently anonymous data can be mined to identify geographical location, and as data analytics tools become more intelligent, personal variables (such as age and gender) may be used to identify participants.

Conclusion

Clearly, the work we do as educational psychologists has changed and will continue to evolve due to the advent of new technologies. An important caveat, given this rapid rate of change, is that much of what we have written here will appear outdated by the time this volume is published, not to mention five years after its publication. What this means is that we have to approach all that we have written with a critical eye and also attempt, even while focusing on the latest tools and techniques, to keep our focus on key ideas that will stand the test of time. It was this concern with relevance that led us to structure this chapter along the eight categories of work. Although the manner in which we go about our business may change, these eight categories will remain important parts of what educational psychologists do.

Looking beyond the eight categories of work, we emphasize three key perspectives on the current literature on technology and its specific role in what we do as educational psychologists. First, among these perspectives is what Salomon and Almog (1998) called the "reciprocal relationship" between technology and educational psychology:

> Technologies and prevailing psychological conceptions of learning, thinking, and instruction have always served and inspired each other in reciprocal ways. On the one hand, technologies in education have served to facilitate and realize the kinds of pedagogies that emanated from the changing zeitgeists and from prevailing psychological conceptions. On the other hand, and possibly only recently, technologies have been imported into education, challenging it and requiring novel psychological explanation and pedagogical justifications. (p. 222)

In other words, Salomon and Almog argue that there is a transactional, dialogic relationship between the psychology of learning and the affordances and constraints of technologies, where each helps define the other (what they have described as "an ongoing duet"). Thus the pedagogical meaning of a technology emerges not just from the tool (and its properties) but rather from its deep integration into the matrix of subject matter, learners, and classroom environments. As Bruce (1997) says, "A technology is a system of people, texts, artifacts, activities, ideology, and cultural meanings" (p. 5).

The second perspective highlights the ways in which technologies and theories of mind have co-evolved over time—either to instantiate our current understandings of learning or, just as importantly, to seek models for thinking about thinking. Our understanding of the human brain and its activity has been consistently influenced by metaphors of the current technology. These include pneumatic/hydraulic metaphors, such as those used by Galen and Descartes, wherein the brain was considered a site for the mixing, storing, and redirection of "spirits" throughout the body to determine behavior and action. With the rise of the Industrial Revolution, new machine metaphors came to be used where the brain was now considered a complex mechanical apparatus with levers, gears, and pulleys. In the early part of the twentieth century, with the rise of telephone networks, the brain came to be seen as a switchboard with inputs, outputs, and signals. More recently, the advent of the digital computer led to the brain being viewed as a device for information processing. The advent of the internet has paralleled visions of the brain as being a networked computer.

The third perspective illuminates how technologies provide important "boundary conditions" to test educational and psychological theories. This involves providing new methodologies and new sources of data to test our theories as well as providing new tools to develop theory and to share our work with others. Technology can also provide novel pedagogical opportunities that offer a new "zone of possibility" (Kereluik, Mishra, Fahnoe, & Terry, 2013, p. 128) beyond our current psychological understandings, explanations, and justifications. Because technologies develop so rapidly, often outpacing developments of our psychological conceptions, technology can pose important conceptual and theoretical challenges for educational psychologists. Suddenly, old and partly dormant issues, such as transfer, intentionality, and mindfulness, can be brought again to the forefront as we develop novel conceptions and understandings of human behavior, learning, and instruction (Salomon & Almog, 1998).

These are truly exciting times for education—in large part distinguished by rapid changes in technology that are changing almost all aspects of our professional lives as educators and educational scholars. We believe that this ongoing duet will continue into the future.

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