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Can Psychology Research Inform Health Information Data Collection?

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Abstract: Conclusions drawn from electronic medical records (EMRs) are only as accurate as the data provided. Recent findings by psychologists and health researchers may help streamline health information data collection and subsequent data analysis. Specifically, four areas will be discussed: (1) Standardization of terms between the patient and the health professionals, (2) Impact of patient inattention and fatigue when responding to health measures, (3) Importance of source labeling within the medical record (e.g., self-administered questionnaire, responded via phone, etc.), (4) Cognitive load on patients when using mobile health technology (e.g., apps, tablets, online patient portal, etc.). Research suggests consideration of these potential biases could provide the patient with a better health care experience, assist the health care provider in diagnosis and treatment, conserve time and resources, and aid researchers as they consider health outcomes.

INTRODUCTION

Electronic medical records (EMRs) offer opportunities to access and analyze unprecedented amounts of health data, including information from laboratory tests, pharmacy records, medical histories, billing information, and immunization records. For much of this data, the potential for psychological biases is relatively low. However, some aspects of the EMR contain patient reported outcomes (PROs) which may be subject to bias (e.g., a patient reporting drinking behavior). These PROs are frequently used by physicians, researchers, and other health care professionals, yet the impact of potential psychological bias on these outcomes is rarely addressed by those concerned with EMRs and health information technology (HIT). The following paper outlines several areas of psychology research that can reduce potential bias in PROs which, in turn, could allow for more streamlined data collection, assist in diagnosis and treatment, aid researchers, and improve the patient experience.

Standardization of Terms

Previous health technology researchers have emphasized the need for standardization of healthcare and medical terms across providers, hospitals, and researchers (Skrocki, 2013). Yet, other opportunities exist for standardization, including standardization and clarity of terms between patients and providers when patients are reporting health information. The patient reported definition of binge drinking, for example, varies by gender and average alcohol use with almost 40% of frequent binge drinkers reporting that males needed to drink 10 or more drinks to be considered a binge drinker (Wechsler & Kuo, 2000). Other definitions of medical terms are also subject to bias, such as expectations about cognitive decline (Connell et al., 2007; Giebel et al., 2015) symptoms of poor mental health (Hinton & Lewis-Fernández, 2011), and the perception of obesity (Paeratakul et al., 2002; Sutcliffe et al., 2015). Social psychologists suggest these differences between patient definitions and health care provider definitions stem from different social or cultural norms (Aarts, & Dijksterhuis, 2003; Sherif, 1936). For example, those who belong to social groups where binge drinking is considered normative (e.g., fraternity groups, colleges where binge drinking is common, etc.) are much more likely to binge drink themselves (Cashin, Presely, & Mielman, 1998) but not necessarily view this behavior as problematic or as meeting the criteria of binge drinking (Wechsler & Kuo, 2000). Similar patterns of bias have been found for obesity (Barnett, 2015; Carnell et al., 2005). When combined, these studies suggest patients may be biased to underreport PROs and that this bias may stem from a wide array of norms—including norms that may not be immediately obvious to the health care professional (e.g., membership in a social club like a fraternity).

These potential biases could be mitigated by having the health professional offer a clear definition to the patient when asking for PROs, such as: “Do you engage in binge drinking? Binge drinking is defined as 5 or more drinks for men

and 4 or more drinks for women in a 2-hour period” (Centers for Disease Control and Prevention, 2015). Research indicates individuals who are given new anchor points or new information (e.g., maximums about binge drinking) are responsive to this new information and use these new anchor points when assessing subsequent situations (Dikemann, Przepiorka, & Rauhut, 2015; Haines & Spear, 1996). Furthermore, data suggest a single intervention-type training session can reduce these types of social and cognitive bias (Morewedge et al., 2015). These studies suggest decreasing response bias and standardizing patient definitions does not require any special tools or costly interventions. Instead, standardization of terms between patients and providers offers many benefits with relatively little cost. Use of properly standardized terms when collecting patient reported outcomes could allow for better patient care and more precise diagnosis. Additionally, introduction of standardized term also offers opportunities for health practitioners to improve future health behaviors by clarifying medical terms for patients.

Patient Fatigue and Concise Measurement

Prior researchers have found the quality of the responses decline as participants grow fatigued or bored with questionnaires. This phenomenon has been referred to as participant or respondent fatigue (Ben-Nun, 2008) and has been documented across a range of populations and survey content. Participants who are fatigued often decline to respond to survey items (Hoerger, 2010), misrepresent or inaccurately report responses in order to complete the survey (Lehnen & Reiss, 1978), or engage in “straight-line” responding where they respond to all the items with the same answer (Galesic & Bosnjak, 2009). Specifically, prior research has found questions at the end of a questionnaire may be responded to differently than if they were at the beginning of the survey (Helgeson & Ursic 1994). Although no absolute rule exists, researchers examining participant fatigue suggest questionnaires of no more than 20 minutes to ensure quality data (Rathod & LaBruna, 2005).

How does one balance the need for quantity of health data and quality of health data? One avenue for decreasing questionnaire length is the use of single-item questionnaires in place of traditional, longer questionnaires. Research examining mental health indicates single-item assessment, e.g., “How would you rate your mental health today?”, can serve as a brief screening tool for those at risk for mental health problems (Hoff, Bruce, Kasl, & Jacobs, 1997; Jang et al., 2012). Researchers have also suggested the use of single-item questions to assess quality of life (Fayers & Hand, 2002), physical activity level (Milton, Bull, & Bauman, 2011), and stress (Elo, Leppänen, & Jahkola, 2003). Historically, single-item measures had been considered psychometrically inferior to longer measures (Allen & Yen, 2006). However, use of single-item visual analog scales when assessing health (i.e., ranging from 0 to 100) are gaining statistical support as they have been found to be reliable over time, offer a range of response alternatives, and offer both discriminant and convergent validity (De Boer, et al., 2004). Financial data also support the use of single-item measures. For example, De Salvo and colleagues (2009) found a single-item measure of general self-rated health predicted future medical expenditures as well as longer, established measures of health. When combined, these studies point toward an approach that may benefit all involved participants. More accurate health information data and shorter surveys provide a better patient experience and streamlining the EMR through concise measurement is cost effective for the provider.

Source Labeling and Questionnaire Administration Format

Patients are asked to respond to self-administered health questionnaires (e.g., paper and pencil forms, completing patient information online through a patient portal), respond to health questions in-person to a health professional, and asked to answer health related questions over the phone. For many health practitioners and researchers, the common assumption is that so long as the patient is disclosing health information to health professionals, the responses will be consistent. As such, the questionnaire administration format should not impact the quality of the data. However, research suggests the participants respond to sensitive questions differently depending on the administration format. Responses to mental health questions are given more positive responses (i.e., better mental health) when answered via phone than when answered in using a self-administered questionnaire (Feveile, Olsen, & Hogh, 2007). Additionally, mental health symptom scores responded to using self-report on pencil and paper are almost double the symptom scores when responding orally to a mental health professional (Wright et al., 2015). Research also indicates that mental health measures are more sensitive to administration format than questions focused solely on physical health (Cheung et al., 2011; Lungenhausen et al., 2007). These inconsistencies in response patterns are likely due to social desirability bias where patients feel there is some correct or “healthy” response and adjust their answer accordingly (Bowling, 2005).

Two possible solutions may minimize the impact of administration format of health questionnaires. First, those collecting health information data and those conducting health research should consider the impact that administration format may have on patient responses. Measures of mental health and mental health related behaviors (e.g., alcohol consumption, recreational drug use, etc.) may be especially vulnerable to underreporting and social desirability bias. As such, questions about mental health should be administered using self-report whenever possible with the patient completing the questionnaire on his or her own in a private setting. Second, EMRs should offer opportunities for labeling the source of the data. Although the administration format of the questionnaires may not be modifiable, plainly labeling how the data were acquired would allow health professionals and researchers to make appropriate comparisons and more accurate diagnoses.

Cognitive Load and Mobile Health Technology

A recent survey conducted in partnership with American Hospital Association's (AHA) Health Forum and the College of Healthcare Information Management Executives (CHIME) reports 79 % of hospitals have online patient portals accessible through an app (Weinstock & Hoppszallern, 2015). Similarly, many hospitals are evaluating the utility of patient data collection using tablets, such as iPads® (e.g., Cook et al., 2014; Kaka et al., 2015). The role of apps and mobile devices for health care practitioners has been examined (e.g., Divall, Camosso-Stefinovic, & Baker, 2013; Segal et al., 2015; Ventola, 2014), yet relatively little research has examined mobile health technology from the patient perspective (for rare exception see Martin et al., 2015). Research from cognitive psychology, however, suggests that patient familiarity or literacy with mobile health technology may significantly impact PROs when using these "new" mobile platforms. Cognitive load theory, for example, suggests that when an individual's working memory becomes too taxed, learning becomes hampered (Sweller, 1994) and the individual may provide inaccurate responses to relatively simple questions (Ashcraft & Kirk, 2001). This tendency to become cognitively overburdened is most likely to occur when the individual views the information as unfamiliar or "new" (Stolovitch, & Keeps, 2006). Research also suggests that individuals can be "primed" to be cognitively overburdened by a task. For example, something as simple as how a health care provider frames mobile health technology can affect how the patient performs when using the technology (e.g., "new, data driven mobile health platform" vs. "a useful health tool") (Chasteen et al., 2005). Finally, research examining working memory indicates an individual who is less cognitively burdened tends to respond to problems using reason (e.g., "I am not sure which button to press—I should ask for help."). Conversely, when the individual is cognitively taxed he or she will respond using emotion (e.g., "I don't know how to use this thing! I quit!") (Shiv & Fedorikhin, 1999).

Assessing patient literacy and familiarity with mobile health technology is uncharted territory. Indeed, to date, only one in-progress dissertation specifically addresses this new research area (Ahmed, 2015). However, the newness of this field does not mean that health care providers should assume that all patients are either, a.) completely adept at using mobile health technology, or b.) completely incapable of utilizing the benefits of mobile health technology. Instead, many patients fall somewhere in the middle of this spectrum with each patient having his or her own set of costs and benefits to using mobile health technology. Additionally, health care providers should be cognizant of different skill levels within the same individual across different mobile technology platforms. For example, patients that are comfortable using online patient portals at a desktop computer may not necessarily be comfortable with a mobile health app or data collection using an iPad® (HealthIT.gov, 2014). The potential for mobile health technology is great, yet the data provided through these platforms hinges on the patient utilizing these services and providing accurate PROs. As such, providers should not make assumptions about patient literacy and familiarity with technology, but should instead ask targeted questions to ensure the patient feels comfortable using the specific mobile health technology in question.

CONCLUSION AND FUTURE DIRECTIONS

While not exhaustive, the following recommendations may reduce bias when collecting patient reported outcomes for EMRs:

- 1.) Be cognizant of social and cultural norms when defining health. When in doubt, define.
- 2.) Keep questionnaires and data collection instruments to 20 minutes or less.
- 3.) Use validated single-item measures whenever possible.
- 4.) Administer sensitive health questions and questions about mental health using self-report questionnaires.
- 5.) Plainly label the source of the patient reported outcome in the EMR.

- 6.) Assess patient familiarity with mobile health technology. Do not assume all patients are comfortable using this “new” technology.

Moving forward, HIT researchers and those that work with EMRs should consider the role of psychology and the inherent biases that occur when requesting PROs. Although patient reported outcomes only comprise a relatively small portion of the data in EMRs, the cost of implementing and utilizing EMRs is high (Fleming et al., 2011). As such, any opportunity to streamline EMR data collection could prove financially beneficial. Additionally, according to a 2013 RAND report, EMRs are underperforming compared to their projected goals (Kellerman & Jones, 2013). Considering psychological biases when collecting patient reported outcomes will not assist in many of the concerns with EMR implementation and utilization (e.g., network security). However, consideration of these biases may assist EMR developers as they work toward adaptive HIT systems that are more user friendly and take social and cognitive aspects of the patient/provider experience into account (Denning, 2013). Finally, previous researchers have examined many of the possible problems with using EMRs (e.g., reduced emotional responsiveness during patient interactions (Margalit et al., 2006)). However, as this paper details, other areas of bias exist, such as bias that occurs before the patient health information is even entered into the EMR. As such, simply acknowledging PROs may be subject to bias could help patients, health practitioners, and health researchers.

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