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Moving Toward a Precision-Based, Personalized Framework for Prevention Science: Introduction to the Special Issue

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Abstract

The goal of this Special Issue is to introduce prevention scientists to an emerging form of health care, called precision medicine. This approach integrates investigation of the mechanisms of disease and health compromising behaviors with prevention, treatment, and cure resolved at the level of the individual. Precision Medicine and its derivative personalized prevention, represents a promising paradigm for prevention science as it accounts for response heterogeneity and guides development of targeted interventions that may enhance program effect sizes. If successfully integrated into prevention science research, personalized prevention is an approach that can inform the development of decision support tools (screening measures, prescriptive algorithms) and enhance the utility of mobile health technologies that will enable practitioners to use personalized consumer data to inform decisions about the best type and/or intensity of a prevention strategy for particular individuals or subgroups of individuals. In this special issue, we present conceptual articles that provide a heuristic framework for precision-based, personalization prevention research and empirical studies that address research questions exemplary of a new generation of precision-based personalized preventive interventions focused on children's mental health, behavioral health, and education.

Scope of the Problem

Over the previous half century, prevention scientists have witnessed an exponential growth in the development, validation and dissemination of preventive interventions designed to reduce the prevalence of mental health problems (e.g., depression, anxiety and aggression) and health-compromising behaviors (e.g., drug abuse, delinquency, bullying, unsafe sexual practices, school dropout, obesity, etc.). First generation prevention programs were typically of the universal type, with intervention strategies offered to reduce risk in the general population. For the most part, these preventive interventions conformed to a fixed prescription format that offered uniform composition, intensity and delivery procedures for all participants regardless of the primacy, quantity, and complexity of putative risk factors

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that may have differed among participants ("one size fits all"). Although these programs produced some benefit, effect sizes on key outcomes were modest with many participants clearly remaining at risk (see Corrieri, Heider, Conrad, et al., 2014; Sandler, Wolchik, Cruden, et al., 2014). Over time, prevention programs have become more precise with inclusion of targeted approaches, i.e., Institute of Medicine [IOM] report (Mrazek & Haggerty, 1994). Selective prevention, for example, targeted subpopulations whose risk was significantly higher than average, as evidenced by biological or psychological vulnerabilities and/or exposures to adverse environmental or social risk factors. Indicated prevention targeted even higher risk persons who had minimal but detectable symptoms foreshadowing a disorder, but not presently meeting diagnostic criteria. Unfortunately, these targeted programs were often unwieldy and costly to deliver, participation and engagement rates were poor, stigma was common, and similar to universal programs, significant but small effect sizes were reported on key outcomes with considerable variability in individual response (see Thibodeau, August, Cicchetti, & Symons, 2016). To date, research studies have provided little insight as to why certain individuals benefit from preventive interventions and offered few clues as to alternative interventions that might be effective for those who fail to benefit. If preventive interventions are to produce greater public health impact, further refinement of proven prevention strategies is needed, as well as design of novel approaches that exact greater precision, specificity and efficiency in their design and delivery.

The Emergence of Precision Medicine in Health Care and Health Care Delivery

In recent years, there has been a call to action to explore personalized approaches in healthcare diagnostics and therapeutics referred to as precision medicine (PM) (e.g., Burke & Psaty, 2007; Leeder & Spielberg, 2009). Leaders at the National Institutes of Health (NIH) have voiced strong support for personalized approaches across various healthcare disciplines (Collins & Varmus, 2015). In support of this approach President Obama unveiled a bold new Precision Medicine Initiative (PMI) in 2015 (www.whitehouse.gov/precision-medicine) to revolutionize how we improve health and treat disease based on the premise that accounting for individual differences in people's genes, environments, and lifestyles will improve both disease prevention and treatment. The White House and NIH have embraced PM as a national priority with $215 million allocated for this initiative in FY2016 and another $309 million in FY2017 (NIH, 2016). An outgrowth of this initiative is the launch of the *"ALL OF US"* Research Program - the largest longitudinal study in the history of the United States (1 million volunteers). This study will serve as a database for biomedical and behavioral research by identifying individual differences in disease etiology and course via a comprehensive information technology infrastructure that will be the vehicle for collecting, analyzing and sharing patient data (Sankar & Parker, 2017).

The emerging field of PM, also referred to as precision healthcare, tailored healthcare, personalized care and patient-centered care offers an approach that if adopted by prevention scientists could significantly boost the impact and uptake of evidence-based preventive interventions. PM involves the use of information about individual-level risk susceptibility factors (underlying mechanisms of disease) to identify drivers of health and illness that are applied to support treatment decision-making and personalized therapy (He, Xia, Shehab, & Wang, 2015). PM fundamentally posits that interventions that are on average marginally beneficial may be administered to maximum effectiveness and safety when the choice of treatment, dosage, or time of delivery is informed by the individual's genetics and biology, environmental exposures, lifestyle preferences and other personalized determinants of outcomes. By assigning interventions to those most likely to benefit, PM can become a powerful tool for a more rational system of care and reducing healthcare disparities (Dankwa-Mullan, Bull, & Sy, 2015).

While the notion of PM has led to great optimism in the treatment of serious medical conditions such as cancer, cardiovascular disorders, and infectious diseases, its contribution to mental health and behavioral health, particularly prevention, remains largely untapped. A comprehensive precision-based prevention approach would emphasize the "what" (which risk factors to target), the "why" (the biological and psychosocial mechanisms that underlie these risk factors, as well as the "how" (e.g., the change strategies that can be offered to modify these mechanisms and the delivery procedures that enhance the accessibility and acceptability of these strategies for individuals). If successfully assimilated into prevention research, the PM approach can inform the development of decision support tools (screening measures, prescriptive algorithms, intervention response indicators) that will enable practitioners to use personalized consumer data to inform decisions about the best type and/or intensity of a prevention strategy for particular individuals or subgroups of individuals. In this special issue, we present conceptual articles that provide a heuristic framework for personalized prevention research and empirical studies that address research questions exemplary of a new generation of precision-based personalized preventive interventions focused on children's mental health, behavioral health, and education.

Elements of a Personalized Prevention Approach

If the concept of personalized prevention is to gain traction in prevention science, key elements of its approach need to be clearly described and illustrated to guide program developers in tailoring existing and new programs. We refer to these elements as *tailoring technologies* and provide several examples. Collins, Murphy, and Bierman (2004) published a seminal article in personalized prevention that suggested that interventions can be tailored in two ways: (1) prior to the start of an intervention with different prevention/treatment components or dosages assigned to different individuals based on each individual's preexisting values on personal characteristics (e.g., risk factors) that predict intervention response; or (2) during the course of an intervention with components or dosages repeatedly adjusted within individuals contingent on assessment of ongoing performance (e.g., intervention response indicators).

The fundamental building block of the former *a priori* approach is the identification of moderators (i.e., variables that predict differential responses to various intervention options). Once identified, these moderators can be translated into empirically-derived decision rules that form the basis for assigning the appropriate component or dose of an intervention to each person, based on the person's values on these moderators (i.e., tailoring variables).

Historically, efforts to identify informative moderators have been largely based on demographic (e.g., age, gender, SES) and descriptive factors (behavioral problems, problem severity, functional impairment). Efforts to use such moderators as a tailoring strategy have produced mixed results (e.g., Dodge, Conduct Problems Prevention Research Group, 2007). Recent work by Conrod and colleagues has demonstrated that personality-based risk factors, such as impulsivity, sensation seeking, hopelessness and anxiety sensitivity are predictive risk factors for adolescent substance misuse (Castellanos-Ryan & Conrod, 2011). Moreover, targeting these factors with brief, focused, skills-based selective-type preventive interventions was found to be effective in preventing escalation in the frequency of drug use and preventing experimentation with new illicit substances over a 24-month period among high risk adolescents (Conrod, Castellanos-Ryan, & Strang, 2010; O'Leary-Barrett, Castellanos-Ryan, Pihl, & Conrod, 2016).

The second approach described by Collins, Murphy, and Bierman (2004) is the adaptive-sequential intervention design that specifies how a component or intensity of an intervention should change over time depending on the person's response to the intervention. Recommendations for change are based on proximal outcomes assessed during the intervention such as desired change on intervention mediators (e.g., decision-making), process variables (e.g., self-efficacy), engagement measures (e.g., compliance) and/or improvement in the distal outcome (e.g., abstinence from drug use). When developing adaptive-sequential intervention strategies, questions that often need to be addressed include the best sequencing of program components when individuals are not responding to a first-line intervention and the best timing of transition from more intensive components to less intensive components or vice versa (i.e., stepped care; Murphy, Oslin, Rush, & Zhu, 2007). The construction and refinement of adaptive strategies is achieved via the sequential multiple assignment randomized trial (SMART; Almirall & Chronis-Toscano, 2016; Lavori & Dawson, 2004; Lei, Nahum-Shani, Lynch, Oslin, & Murphy, 2012). In SMART, participants are randomized multiple times at critical decision points. For example, an individual may be randomized initially to one of two intervention options and then randomized a second time to two or more second tier intervention options once it is known if the individual is a responder or non-responder to the initial option. Much of the formative work with SMARTs has been conducted in the treatment of chronic disease such as substance use disorders. Its application to prevention is best illustrated by recent work of August, Piehler, and Bloomquist (2016), who sought to develop adaptive intervention strategies to preempt the risk trajectories of youth identified by law enforcement as early juvenile offenders and entered into a diversion program with the goal to prevent the progression to a serious conduct disorder.

Additional tailoring technologies have emerged since the publication of the Collins, Murphy, and Bierman (2004) article. An important and emerging aspect of personalized healthcare, and prevention in particular, is the active engagement of participants in making decisions about the services they receive. Given the existence of various prevention approaches, it is likely that consumers will have preferred options (Aita, McIlvain, Backer, McVea, & Crabtree, 2005). It stands to reason, that offering parents a voice in decisions about interventions for their children can increase healthy outcomes (Cunningham, 2007). Gewirtz and colleagues have initiated a program of research that examines the impact of affording parents their preferred ‘choice’ of intervention modality in a parent training intervention (He, Gewirtz, Lee, Morrell, & August, 2016). Although multiple potential designs have been utilized for examining choice, a doubly randomized preference trial is the optimal design for examining whether providing choice of interventions improves adherence and/or post-treatment outcomes (Marcus, Stuart, Wang, Shadish, & Steiner, 2012). Understanding consumer preferences in prevention science is at an inchoate stage, with very little existing research to inform how and why prevention interventions might be tailored to accommodate families’ choices.

Last, a personalized prevention approach seeks to leverage advances in personalized devises (e.g., smartphones, wearable GPS units and electronic data capture tools and related mobile technologies) to improved accessibility and acceptability of preventive interventions and enable real-time assessment of influences on personal health. Mobile technologies are rapidly evolving as a method of delivering brief interventions that can be tailored to the individual throughout the intervention. For example, smartphone use has been widely adopted across various client groups and appears greater among those populations most in need of these interventions. Importantly, mobile interventions have the capacity to provide just-in-time, interactive and adaptive frameworks. As sensing technologies are integrated within the mobile phone, health behavior change interventions can be delivered based not only on self-reports and time/location parameters but also on psychophysiological state, social context, activity levels and behavioral patterns. The availability of these complex and frequent data inputs provides the potential to deliver health behavior interventions tailored not only to the person’s baseline characteristics but also to her/his frequently changing behaviors and environmental contexts. As such, these technologies can help overcome barriers to intervention, including cost, availability of counselors, scheduling logistics, transportation, and stigma.

Premise for this Special Issue

Articles in this special issue were originally presented as invited presentations at the symposium: “Moving Toward Precision Healthcare in Children’s Mental Health: New Perspectives, Methodologies, and Technologies in Therapeutics and Prevention”, sponsored by the Institute for Translational Research in Children’s Mental Health at the University of Minnesota in October, 2016. The articles include conceptual foundations, original empirical studies, innovative methodological and analytical approaches and emerging technologies that illustrate the state of precision-based, personalized mental health, behavioral health, and education within the field of prevention science. The research described in this special issue features a transdisciplinary perspective that brings together the work of clinical child psychologists, translational behavior scientists, intervention scientists, and methodologists all of whom share a common conceptual framework that seeks to synthesize theoretical and methodological perspectives to address personalized prevention. In this special issue we provide examples of (a) personalized interventions informed by new discoveries in neuroscience, (b) innovative experimental designs for increasing specificity and precision in the targets of prevention programs, and (c) utilization of high resolution measurement (i.e., ecological momentary assessment), and social media (e.g., Facebook) that capitalize on delivery system reforms (e.g., just-in-time-adaptive interventions).

Topics of the Special Issue

The first set of articles in this special issue illustrate foundational elements of a precision-based prevention-focused personalized approach. The lead article by Fishbein and Dariotis (2017) begins with presentation of a translational framework to guide the construction of precision-based interventions, the conduct of comparative effectiveness trials and the incorporation of prevention programs into routine practice settings. Central to this approach is targeting children and youth with altered trajectories of brain development, particularly affecting neural circuitry that undergirds emotion and behavioral self-regulation. This approach relies on the elucidation of various biologic and psychosocial mechanisms that underpin risk for mental health problems and health compromising behaviors with the understanding that individual differences in the mechanisms that undergird these problems and behaviors likely result in variable response to interventions. Identifying these individual differences in response can guide intervention tailoring by matching individuals with the type and dosage of intervention that best fits their risk profiles. The article provides illustrations of this approach using neurocognitive (self-regulatory) and psychosocial generators of risk behaviors. Following presentation of this framework is a discussion of the translation of this knowledge to the refinement of existing programs as well as the development of novel programs by targeting the aforementioned generators of risk behaviors. To further optimize prevention effects, the authors present a number of innovative precision-based research designs that seek to identify "who" is responding best to an intervention and "why". For example, effectiveness-implementation hybrid designs blend experimental design components that assess intervention effectiveness research and implementation factors (e.g., provider and service setting behaviors) that influence uptake and quality of delivery (Curran, Bauer, Mittman, et al., 2012). Other examples include the Multi-Phase Optimization Strategy (MOST; Collins, 2018), the sequential multiple assignment randomization trial (SMART; Lei et al., 2012), brief interventions (e.g., motivational interviewing; Miller & Rollnick, 2002) and the Screening, Brief Intervention and Referral to Treatment (SBIRT; Barbor, McRee, Kassebaum, et al., 2007).

The *sine qua non* of personalized prevention is heterogeneity of treatment effects, that is, the existence of between-person differences in the relative effectiveness of different types of interventions (i.e., "what works best for whom"). The article by Howe (2017) presents a causal inference framework to explore two logically distinct forms of preventive effects heterogeneity that may inform development of personalized prevention programs. One form is causal interaction involving two separate malleable action mechanisms (i.e., behavior change strategies that prevent future disorder by altering etiologic mechanisms) that combine to yield non-additive effects. When etiologic and action research indicates that these mechanisms operate differently for different people personalizing prevention programs may be required. For example, the ability to recognize emotionally-charged situations may be a necessary prelude to building emotion regulation skills such as coping self-talk. The other form, referred to as effect heterogeneity, i.e., effect moderation involves variation in causal structure indexed by stable characteristics (i.e., moderators) of populations or contexts. In this case, the question of interest may be whether differences in a personality trait may index differences in other causal variables. For example, impulsivity can index differences in exposure to deviant peer influence, with high impulsive youth exposed to higher levels than low impulsive youth. Effect moderation may be of particular importance given that it can provide information concerning which groups are most likely to benefit from a prevention program. The article goes on to discuss the baseline target moderated mediation (BTMM) design that uses theoretically-informed baseline target moderators to strengthen causal inference. Identification of informative baseline target moderators can inform personalization of prevention programs opening the door to tailoring interventions to specific target moderators.

The third article in this set is by Glenn, Lochman, Dishon, et al. (2018) who report results from an intervention trial that examined whether psychophysiological characteristics of the child predicted the child's response to two intervention formats of the Coping Power Program. Specifically, the authors examined moderation using aggressive children's autonomic nervous system indices (parasympathetic and sympathetic self-regulation) to differentially predict response to either a group- or individual-focused delivery format of the Coping Power Program. Study results showed that indices of parasympathetic functioning interacted with intervention format, but indices of sympathetic functioning did not. Highly aggressive children with low levels of respiratory sinus arrhythmia (RSA) benefitted from the individual format whereas those assigned to group format showed no change in aggressive behavior. For highly aggressive children with low RSA, the individual format was more effective in reducing proactive aggression than the group format. For children with high RSA, initial level of aggression showed no differential effect with both formats showing reductions in teacher-rated aggression. This suggested that skin conductance level (SCL) is a more general predictor to response to the Coping Power Program. Contrary to prediction, SCL predicted intervention responding regardless of intervention format with lower baseline SCL associated with greater reductions in teacher-rated proactive aggression. The Glenn et al. study is a prototype of the research designs necessary to resolve the intervention response heterogeneity that exists for many behavioral conditions with the goal of tailoring (personalize) preventive interventions to 'precise' characteristics of individuals.

A second set of four articles in this special issue report empirical findings from basic science and preventive intervention trials that inform the field of personalized prevention. These studies use innovative methods, and/or designs to identify unique subgroups of individuals who benefit more, or less from prevention interventions. The article by Dishion, Mun, Ha, and Tein (2018) used latent profile analysis (LPA) to understand how adolescent interpersonal relationships predict behavioral and emotional health in early adulthood. Applying multiple methods (coded audiotapes of the Five Minute Speech Sample, and coded videotaped observations of interactions with friends and family), LPA revealed three distinct subclasses of youth. The "Healthy Relationships" group, with low levels of observed deviant and drug talk in adolescence, showed low levels of early adulthood substance use, violence, and mental health problems. The "Disaffected" group, with high levels of drug use discussion with peers and negative talk about parents in adolescence, showed higher risk of depression and substance use in early adulthood, while the "antisocial" groups with high levels of observed coercion with family and friends, coupled with deviant and drug use talk in adolescence, showed increased risk of violence and substance use in early adulthood. LPA provides an opportunity to further understand the nuances of risk in interpersonal interactions that may be harnessed in interventions to prevent subsequent problem behaviors.

The next two articles in this set report outcome data from prevention trials targeting the tailoring of a particular aspect of the intervention or its delivery to the needs or preferences of the participants. Garcia-Huidobro and colleagues report results from a pilot study of an adaptive parenting program that also implemented adaptive recruitment of Latino immigrant families in order to increase participation of fathers in two parent families (Garcia-Huidobro, Diaspro-Higuera, Palma, et al., 2018). The adaptive recruitment strategy (provided only for two parent families) featured home visits, compared with the standard recruitment strategy of print or electronic flyers. The group-based parenting intervention provided an additional, one-on-one adaptive component (online videos plus telephone calls) for parents who did not attend group sessions. The adaptive recruitment strategy led to 73% of fathers participating in the program, compared to a prior study of the same program in which only 13% of families had two parents enrolled (Allen, Hurtado, Garcia-Huidobro, et al., 2017). Similarly, the authors attribute the additional adaptive intervention component to strengthening overall program use, with fathers more frequently using the adaptive (1:1) component than were mothers. These types of adaptive intervention strategies have the potential to increase participation of difficult-to-reach groups; the selective use of these strategies also conserves cost and manpower resources.

The study by Estrada, Lee, Wagstaff, et al. (2018) reports on the effectiveness of a particular intervention format – web-based– that has the capacity for far higher reach than traditional in-person interventions, and that ultimately could constitute one type of intervention format in an adaptive prevention trial. This study evaluated eHealth *Familias Unidas*, an online adaptation of a well-validated family intervention to prevent substance use and related risk behaviors in middle school students. Families were assigned to the eHealth *Familias Unidas* intervention or to 'prevention as usual' – a classroom based HIV prevention curriculum (likely also provided to youth in the intervention group). The 12-session intervention included eight online, pre-recorded group sessions that parents could watch at their convenience, and four parent-adolescent sessions facilitated by a staff member over WebEx teleconferencing software. Outcome analyses at posttest (3 months post baseline) and at 9 months follow-up, indicated significant treatment effects on drug use, prescription drug use, and cigarette use. The results of this study could pave the way for an adaptive intervention trial of *Familias Unidas* to understand which types of intervention format are most effective for which types of families.

As noted earlier in the Introduction to this special issue, most personalization research is informed by need-based moderators (i.e. putative tailoring variables related to a specific risk or vulnerability factors). The importance of incorporating individuals' preferences in intervention research has been identified as a key direction by the National Institute of Mental Health for some time (NIMH, 1998). A core tenet of this personalization strategy is to empower consumers to be active decision-makers regarding their care. Preference studies address this issue by focusing on whether and how addressing participants' preferences can improve adherence and benefit from prevention interventions. The final article in this set by Gewirtz and colleagues presents findings from a randomized preference trial conducted in community clinics in Michigan (Gewirtz, Lee, August, & He, 2018). Families presenting for services to address children's conduct problems were recruited and randomized to 'choice' or 'no choice' experimental conditions. Those assigned to the choice condition could pick from one of four interventions: a multi-family parenting group, clinic-based individual parent training, home-based individual parent training, and child supportive psychotherapy. The three parenting interventions were all Parent Management Training-Oregon (now known as GenerationPMTO) interventions. Families assigned to the 'no choice' condition were again randomized, to one of the above four intervention conditions. Outcome intent-to-treat analyses of child behavioral adjustment gathered from parents and teachers six months following discharge indicated partial support for the effects of choice: teacher-reported improvements in child hyperactivity/inattention problems favored the choice condition. Prior analyses also showed improved adherence among those in the choice condition (He, Gewirtz, Lee, Morrell, & August, 2016). Contrary to hypotheses, however, teacher reports of hyperactivity/inattention problems also favored children in the no-choice condition assigned to child psychotherapy. Preference studies, of which there are few, provide an opportunity for further understanding of how to strengthen adherence and benefit by empowering consumers to make decisions about their care.

The final set of two articles illustrate novel methodological, technical and analytical advances that demonstrate the potential applications of a personalized framework. The article by Connor (2017) focuses on the prevention of reading problems in K-3rd grade students via a novel technology, Assessment-2-Instruction (A2i), which personalizes literacy instruction via a teacher professional support system in which teachers use assessment data to guide instruction. This technology was motivated by earlier work that revealed child X instruction effects on reading performance. For example, individual differences in the primacy of code-focused versus meaning-focused reading skills interacted with instructional methods. Students possessing weak decoding skills showed greater gains when teachers focused on phonics and fluent sight word reading, whereas children with stronger decoding skills in classrooms using whole language techniques made weaker gains. To elucidate causal effects, a series of randomized trials was conducted to test the effects of personalized instruction strategy using the A2i online technology. This technology was designed to help teachers use assessment results for each student to plan and implement personalized face-to-face computer assisted instruction in the classroom. Computer-based algorithms were generated that computed recommended amounts for each of four types of literacy instruction: teacher-managed/code-focused, teacher-managed/meaning-focused, child-managed/code-focused, and child-managed/meaning-focused. In addition, grouping algorithms placed children with similar reading skills together. The results of this research demonstrated that personalized literacy instruction outperformed traditional instruction effects over a period extending from 1st through 3rd grades yielding a large effect (d=.7) which translated to a full grade-equivalent advantage on standardized test scores.

The article by Luers, Klasnja, and Murphy (2018) features a novel type of mobile health (mHealth) technology called just-in-time adaptive interventions (JITAIs). The JITAI adapts over time (e.g., minutes, hours, days) in response to an individual's behavior health issues (e.g., alcohol use, smoking, physical activity), context (e.g., driving a car, attending a meeting, taking a walk), and physiological and psychological states (e.g., mood, stress level). The goal is to accommodate to an immediate need for support by effecting positive behavioral change at precisely the time it is most needed (see Nahum-Shani, Hekler, & Spruijt-Metz, 2015). Components of the JITAI include “pull” components in which individuals decide at will when to engage an intervention (presumably a time of most need), and “push” components that are delivered by an intervention devise such as a text message to engage in emotion regulation (deep breathing) exercises when experiencing a stressful moment. The present paper focuses specifically on the “push” component and illustrates a method (i.e., micro-randomized trial: MRT) which analyzes longitudinal data to examine whether a push component has an effect, how that effect varies over time, and how, for example, that effect might be influenced by an individual’s stress level at the moment of delivery. In an MRT, participants are randomly assigned to different versions of a given intervention component at each of many decision points when it might be appropriate to deliver the component. By randomizing participants many times, one can estimate the standardized causal effects of time-varying mobile health intervention components as well as moderated effects of these components. The evidence from micro-randomized trials can be of significant help to prevention scientists by increasing precision in the selection of which intervention components should be included in an mHealth intervention and when those components should be provided to specific people to determine what would be most beneficial (i.e., vulnerability/opportunity) and least burdensome (i.e., receptivity) for each individual.

Completing the special issue, Ridenour (2018) provides a commentary that briefly describes the PM initiative and its general principles. An argument is presented for bringing these principles into prevention science and discusses how the articles in this special issue align with and advance those principles within a prevention science framework.

Concluding Remarks

It is the goal of this special issue to introduce prevention scientists to precision medicine (PM), an emerging form of healthcare. PM harnesses large amounts of data available from individuals and uses computational tools to make decisions and formulate practices uniquely tailored to individuals based on their biology, environmental exposures, lifestyles and healthcare preferences. PM and its derivative personalized prevention, represents a promising paradigm for prevention science. The potential payoffs could be substantial. As eloquently stated by Shoham and Insel (2011), “without better understanding of who benefits from what type of prevention strategies, we run the risk of ‘shooting in the dark’ and hitting targets indiscriminately” (p.480). This approach is supported by rapidly increasing scientific insight into the origins of individual differences among people (preexisting risk characteristics), and a corresponding ambition to build this new knowledge into the development of more effective, efficient, and affordable interventions. Identifying the personal characteristics and/or preferences of youth and families for whom existing interventions are less effective and developing alternatives that are tailored to the characteristics and preferences of individuals may be important for improving the overall effectiveness and value of these interventions. Our vision is that personalized prevention will create exciting possibilities for reaching wider swaths of people with preventive healthcare including marginalized families. Inspired by the promise of PM, we hope to leverage and capitalize on new knowledge to design and implement preventive interventions that optimize care and reduce or eliminate health disparities among diverse, underserved populations. We seek to promote broad service reform across youth-serving systems-of-care via the development of personalized interventions that are more powerful and more cost effective than existing "one-size-fits-all" approaches.

The articles presented in this special issue provide examples of what the next generation of preventive interventions may encompass, i.e., interventions that are tailored in accordance with unique characteristics such as indicators of risk and resilience and healthcare cognitions that are indicators of preferences of individuals, families, and communities. Emerging discoveries in genetics, epigenetics, neurosciences and various 'omics-based technologies (e.g., proteomics, metabolomics) are revealing 'under the skin' drivers of mental health disorders and health compromising behaviors which moderate and mediate prevention effectiveness. These moderators and mediators may in turn, reveal targets that enable preventive interventions to cross the 'skin barrier' such as mindfulness techniques that work to regulate autonomic nervous functioning and reduce stress.

Another frontier is discovering new ways to improve individual's adherence to preventive interventions, which is essential for effectiveness. Understanding the psychological, social and economic factors that influence how individuals make decisions about the type of health care they prefer may pave the way for developing decision aids that inform individuals on choosing prevention strategies that are in their best interest (Wills & Holmes-Rovner, 2006). The evolution of digital technologies (e.g., smartphone apps) and wearables to enable real-time assessment of influences on personal health as well as the delivery of brief interventions at the moment they are most needed holds considerable promise (Luxton, McCann, Bush, Mishkind, & Reger, 2011). Finally, while personalized prevention can aim to change individual behavior, it can also precisely target groups or communities by modifying prevention delivery systems, instituting targeted policy or via macro-environmental changes that differ from one community to the next (Valente, 2012). In this respect, personalized prevention will need to converge with implementation science to develop strategies to adopt, implement, scale-up, and sustain preventive interventions at the community level.

Last, we believe that personalized prevention could markedly alter the landscape of prevention science research and practice by providing new methods for risk assessment using complex "big data" (i.e., precision analytics) to open new avenues of prevention research. Data accessed from multiple sources such as genetic and neuroscience studies, smartphone devices and social media, and sensor technologies along with data available from systems of care (e.g., primary care, child welfare), criminal justice, and education can be merged and integrated for their decision-making potential. A variety of statistical techniques from data mining, predictive modeling, and machine learning are available to analyze these data to make predictions about future risk status. This can lead directly to new approaches to tailor interventions to individuals. The articles presented in this special issue represent starting points in exciting new directions for prevention science. As such, they represent new foci for future research.

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