Digital Mental Health—Breaking a Lance for Prevention

WELCOME to the last issue of IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS (TCSS) of 2022. In this issue, we publish a Special Issue on Advanced Cognitive Computing for Data-Driven Computational Social Systems, which includes 23 articles. Moreover, we also would like to share some of our opinions and perspectives on "Digital Mental Health—Breaking a Lance for Prevention."

I. DIGITAL MENTAL HEALTH—BREAKING A LANCE FOR PREVENTION

Mental illnesses are on the rise with a lifetime prevalence of 20%–25% [1] and showed a further increase during the Covid-19 Pandemic [2]. The most frequent disorders are depression, anxiety, and substance or alcohol abuse-related disorders. Besides the great personal burden caused by mental disorders, they cause substantial economic costs due to sick leaves and early retirements. Especially an early onset of mental illness is critical: suffering from a psychiatric disorder during childhood and adolescence greatly interferes with developmental tasks (as building social relationships, and academic achievements) [3], [4] and is associated with a high probability of chronification until adulthood [5]. In contrast to such developments stands the low supply, uptake, and high numbers of nonresponders or relapse in the treatment of psychological disorders [6], [7]. Here, we first motivate why prevention can be an urgently needed game changer, and how it could best be supported by artificial intelligence.

A. Why Prevention Is Crucial

The question arises, and it is a pressing one, if mental disorders are preventable in the first place? Since the 1980s, the World Health Organization declares prevention a public health interest. The etiology of psychopathology is mainly understood as result of a certain nature and nurture interaction. A vast body of research has been conducted to understand such mechanisms precisely. For instance, according to the often postulated diathesis-stress model [8], a mental illness develops not only due to a person's diathesis or vulnerability (like a genetical predisposition and certain personality traits) but due to additional stressors (like loss of job and marital problems). A mental illness would only develop, in case an individual does not obtain sufficient coping strategies (like positive thinking, active problem solving, and social support) to cope with a such stressors. On the other hand, this model also shows that, even if a person has a low vulnerability to develop a mental illness, a high amount of stressors may anyhow lead to psychological problems. Hence, increasing resilience to buffer potential stressors may prevent mental illness, or both, people with low and high vulnerabilities. This may sound like an easy goal to reach, but unfortunately, research on prevention and other prevention attempts is scarce and showed mostly small to moderate effects, e.g., in the prevention of depression [9] even in high-risk groups as the offspring of parents with depression. The latter group is three to six times more likely to develop a mental disorder, due to their high biological risk and the multiple stressors they face due to their parents' depression. In a meta-analysis, there were only seven independent trials identified worldwide that evaluated a preventive intervention in this high-risk group with small to moderate effects on the onset of depression and depressive symptoms that diminished over time [10]. In addition, few studies investigated mediators and moderators and those who did showed very heterogeneous results. Hence, research has shown that mental illness can be prevented and symptoms decreased, but there is no satisfying response for prevention, and mechanisms to increase resilience are poorly understood. Further research is needed to better understand the pathways leading to a mental illness on a personal level and improve preventive interventions. Another option is the early recognition of mental illness to offer as early as possible an adequate treatment for at-risk individuals and especially children and adolescents. Ideally, the most relevant markers for mental illness would be identified as early as possible on an individual basis.

B. Computationally Supporting Prevention

So what can be done to predict mental health disorders and sense and rightfully interpret earliest warning signs of mental disorders by aid of artificial intelligence (AI)? The field of affective computing offers an arsenal of options to monitor affective and further behavior such as by the sound of the voice, the choice of words in speaking and writing, the facial expression, body pose and gestures, gait, up to physiological signals including brain–computer interfaces [11]. In addition, smartphone sensors and usage data as well as other wearables and even devices in the Internet of Things (IoT) have been successfully exploited to measure mental health [12], [13]. However, the challenge of prevention lies in recognizing first warning signs as soon as possible, rather than to merely diagnose or measure mid-to-late-stage mental health issues.

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To this end, first, novelty detection seems a straightforward, albeit less informative option. In other words, trends and changes in affect, mood, or behavior could be automatically assessed. Potentially, no labeled training data would be needed for such a mere "before–after" comparison. Suited potent approaches exits, such as by deep autoencoders that measure the distance between input and output [14] after training on the "usual" affect and behavior data such as the named sound of voice, movement, facial expression, smartphone usage data, etc. Ideally, such an approach would only detect significant affect and behavior changes. This would merely be a warning for caretakers, or therapists without further information on a potential specific disease state, yet could support very early counter-actions.

Second, and more sophisticated, appears the collection of data in retrospect of such already affected by mental health disorders to train systems for future earlier warnings. Likewise, once a data collection participating person's diagnosis is known, one can try to recapture earlier audio, video, text, and further recordings from earlier times of the affected individual. This then may allow to train systems to self-learn early markers. Success of this principle has been shown amongst other for Fragile-X and Rett-Syndrome [15]. However, the approach comes with considerable challenges, as earlier personal data material is often only available in discontinuous time intervals and often stems from mixed recording hardware or infrastructure and different quality levels. For example, looking backward in time for one's early changes in behavior cues may include exploitation of audio and video tape recordings, and digital recordings with increasing (image) resolution and quality owing to the development of technology over the years.

Third, one could target to automatically identify risk factors. As a first simple step, this may include usage of simple questionnaires such as for genetically inherited vulnerabilities or "stress" factors that may trigger mental health diseases. Some risk factors, however, may also be automatically identified by AI and in their sum give supportive warning indications. Many different models exist that could guide the choice of accordingly suited factors and the modeling of mental health risk status. Such models include the biopsychosocial model (BPS—biological, psychological, and social factors), attachment theory, the biomedical model, biopsychological model, or evolutionary psychology. The above-named BPS-related diathesis, i.e., vulnerability—stress model presumes—as outlined—varying degrees of personal vulnerability toward mental disorders in the presence of stress as potential cause of mental health disorders and is the basis of an example of AI support potential in the following. The sources of vulnerabilities include biological (e.g., genetics such as Huntington's disease, prenatal damage, infections and long-term physical health conditions, toxin exposure and substance abuse, head and brain injuries or defects, and epilepsy) [16], personality-relation [17], and cognitive states (e.g., anxiety or emotion [18]). As mentioned, several, if not most of these risk factors could be assessed by means of AI. Opposed to vulnerability are protective factors that could positively reduce the risk of mental health diseases' outbreak. Knowledge of their absence or breakaway could similarly be noted partially in an automated manner, such as personal limited socioemotional competence, a degrading family relationship and lack or degradation of a peer environment, or lack of physical exercise. In particular, low-stress coping strategies increase the risk for mental illness as maladaptive emotion regulation strategies (e.g., rumination, withdrawal, suppression, and negative thinking) [19]. In addition, one could attempt to automatically measure existent stress "triggers" impacting an individual such as specific life events, or emotional stress as given, e.g., by poor physical health, marital, parental, work, and socioeconomic status worries [20]. Finally, comorbidity of mental health disorders can often be a cue, and can again partially be accessed by AI. As an example, major depressive disorder's main comorbidity includes substance use disorder, anxiety disorder, and personality disorder [21]. In Table I, we summarise these risk factors and point to a selected existing related computational modeling, each, that could be a starting point to assess these automatically. The idea here is to demonstrate that mental health risk factors could be largely recognized automatically. Personal devices such as smartphones are already equipped with a multitude of sensors and possess an abundance of personal information. Analyzing such information to identify risk factors automatically could be realized on a higher level and then combined for an overall assessment of the risk to lead to earliest possible prevention strategies. Note that other categorizations of factors then listed and shown here can be chosen and exist in the literature; further, partial overlap exists across chosen groups—the purpose here is mainly to showcase starting points of AI-based supportive preventive mental health disorder risk assessment that appears already feasible.

TABLE I

EXAMPLE FOR A GUIDELINE FOR PREVENTION OF MENTAL DISORDERS SUPPORTED BY MEANS OF ARTIFICIAL INTELLIGENCE (AI). FOUNDATION IS THE DIATHESIS (VULNERABILITY) STRESS MODEL. GIVEN ARE MENTAL HEALTH DISORDER DEVELOPMENT RISK FACTORS BY GROUP: **V**ULNERABILITY, AND **P** MINUS, I.E., ABSENT OR DEGRADED PROTECTION AS WELL AS **S** PLUS STRESS, AND **C** PLUS COMORBIDITY. FURTHER GIVEN ARE ONE EXAMPLE EACH OF INDIVIDUAL FACTORS THAT WERE ALREADY SUCCESSFULLY RECOGNISED BY AI (REFERENCE GIVEN), ALBEIT USUALLY NOT IN THE PRESENT TARGET CONTEXT OF MENTAL HEALTH DISORDER PREVENTION. AN ABUNDANCE OF FURTHER EXAMPLES EXISTS—THE CHOSEN ONES MERELY SERVE FOR INSPIRATORY ILLUSTRATION OF FEASIBILITY

Group : Factor	**Example Recognition by AI**
V : Biological	Epilepsy [22]
V : Personality	Personality Traits (OCEAN) [23]
V : Cognitive	Emotion [24]
P : -Protection	(Lack of) Physical Exercise [25]
S : +Stress	Marital Problems [26]
C : +Comorbidity	Anxiety Disorder [27]

As outlined, other groupings could be chosen and further risk factors could be added such as biological: genetic, neurological, stress and smoking during pregnancy, premature delivery, low birth weight, stress-reactivity (HPA-axis);

predisposition; personality: temperament as child, insecure attachment, cognitive and social skills, self-esteem, personality traits (like neuroticism); environmental: child-parent-interaction, social support, family conflicts (violence), low income, parental disorders and conflicts, professional care infrastructure (availability and quality of professional care); life events: accidents, divorce, job loss, other health issues, death/illness of a beloved person and furthermore. The point is that psychological research offers a multitude of guiding models and factors which can already be automatically recognized to lead to an overarching risk assessment in real-time—potentially ready for everyone, everywhere, and in real-time.

C. Conclusion

We "broke a lance" stressing the massive potential and importance of earliest possible prevention of mental health issues suggesting ways of exploiting artificial intelligence and digital health means to best support this ambitious goal. After distilling from the sparse existent body of literature that this is being a largely untapped area, we suggested concretely three main avenues: 1) detection of novelty in the sense of affect and behavior or life circumstance change on the potentially easiest to implement, yet least informative end; 2) training AI systems from retrospective diagnosed patients' data for future earlier recognition and prevention, which appears promising, but comes at technical challenges given the usual sparseness and diversity of such earlier material such as a depressive diagnosed young adult's childhood home recordings or usage data track of smart devices; and 3) the detection of risk factors ideally mixed between questionnaire-based assessment capturing, for example, genetic indicators with affective, behavioral, health, situational, and further ones assessed automatically by AI. Put together, and exploiting a plurality of information sources such as smart devices, wearables, and IoT sensors, among communication and social network analyses, it appears indeed promising that prevention is a near-future option recognizing a multitude of risk factors for mental health automatically and potentially ubiquitously to lead to a real-time personalized mental health risk assessment for prevention.

With the implementation of such an approach obviously come not only massive ethical, and legal challenges but also social implications such as ideally leading to a healthier society and live for the masses—let us design this future carefully.

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