Topical: Intelligent Meta-Learning Inferential Social Robotic and Virtual Space-Medicine Clinicians

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Abstract

Emerging human-operated telemedicine as well as personable (semi)autonomous social robotic and virtual digibot therapists provide powerful clinical and field/flight-situation tools for surveilling, diagnosing, and treating both physical and mental health crises of inaccessible, remote patients on Earth and elsewhere. Smart robotic and virtual therapists, which exploit continuing advances in artificial intelligence, neuromorphic architectures, animate embodied platforms, merged reality, and other technologies, may especially become ideal instruments to help optimize cognitive-emotional restructuring of astronauts suffering from space-related neuropsychiatric disease and injury, including mood, affect, and anxiety symptoms of any potential severity and pathophysiology. Appreciation of precise, custom neuropsychiatric healthcare through use of new or repurposed assistive meta-learning inferential medical technologies will reveal deeper insights about illness states expressed by astronauts and will help guide, over the decadal period, necessary biomedical research, technology development, and ethics for improved astronaut health, wellbeing, and performance in extreme space and extraterrestrial environments required for achieving near-term manned solar system exploration and habitation objectives.

1. Introduction

Spaceflight-engaged astronauts must often perform with sustained high physical, mental, emotional, and social proficiency to satisfactorily begin and complete even routine daily mission duties and habitation needs in nonterrestrial environments. Stresses caused by constant extreme-environment exposure, such as high-dose cosmic radiation, microgavity, and social isolation or crowding in confined operational locations, intensify risks to the health, safety, and wellbeing of astronauts and further jeopardize already challenging mission goals and outcomes. Accordingly, the 2020 National Aeronautics and Space Administration (NASA) Technology Taxonomy roadmap and 2021 NASA Human Research Program Integrated Research Plan continue to underscore the need for research, development, and application of technologies and methods that improve human health, performance, life support, and habitation in space and extraterrestrial environments to support and expand NASA's goals for manned near-to-deep solar system exploration. Specific areas of interest include, among other categories, medical diagnosis and prognosis, prevention and countermeasures, behavioral health and performance, contactless and wearable human health and performance monitoring, long-duration health, and system transformative health and performance concepts. These areas of emphasis are surveyed here in the context of neuropsychiatric insult, such as mood, affect, anxiety, personality, and psychosis disorders [1-10], due to alterations in astronaut neurobiology and psychology associated with spaceflight, space gateway, and nonterran satellite/planetary surface conditions, including those expected of the lunar Artemis Program within the next five to ten years. In particular, state-of-art, emerging, and next-generation artificially intelligent social robotic and virtual digibot space medicine clinicians are considered as instruments to mitigate negative space-induced effects on astronaut mental health, wellbeing, and performance. Such efforts moreover benefit the advancement of contemporary practices and policies for Earth-based in-clinic and telemedicine approaches for more effective surveillance, prophylaxis/intervention, treatment, and compliance strategies leading to greater positive patient outcomes over the target decade.

Within a modern framework of artificial intelligence (AI)/machine learning (ML) state-of-art, ongoing attempts at building, launching, and employing Earth- and space-based onsite or remote assistive surrogate medical technologies, such as surgical robots, psychotherapeutic digibots, and smart wearables, highlight the difficulties in realizing truly human-like operational features for seamless operated (open loop), semi-autonomous (open-closed loop), or autonomous (closed loop) hardware-software systems [11-18]. These sorts of features, including simulated personality, causal reasoning, emotion, empathy, and other traits [11,12,14-16,19-39], show tremendous science-backed promise for augmenting real-time health-promoting interactions between precise supercomputing artificial theragnostic agents and human patients. Personable clinical surrogate technologies nonetheless remain comparably primitive in their emulation of humans. Expert appraisals further raise concerns over when many marketed consumer technologies will begin providing affordable, safe, and efficacious custom theragnostic outcomes with secure data handling, as imposed by clinical regulatory guidelines for civilian patient-information privacy (e.g., the United States (US) Health Insurance Portability and Accountability Act and Health Information Technology for Economic and Clinical Health Act and the European General Data Protection Regulation). Consumers, patient stakeholders and advocates, government regulators, and health-industry professionals often recognize smart products from IBM Watson Health, Google Health, Amazon Care, and Apple as benchmark-setting voice and/or text interactive supercomputing agents for real-time, inferential, and personable mobile, home, or clinical environment digital healthcare solutions. Such computational platforms and applications render custom diagnoses, prognoses, and prescribed treatment courses through high performance AI/ML-powered federated learning, causal inference, and transfer learning, which depend on trained deep feature detection and extraction, dimensionality reduction and blending, statistical predictive/attributional modeling, and additional processing of patient data and related information siloed in cloud and/or in onsite cyberinfrastructure [cf. 11-14,17,18,40,41]. But, performance ratings falling well below healthcare-industry standards for product reliability and, therefore, medical utility and economic viability have generated considerable technology-ecosystem volatility over recent years in the private sector, leaving costly long-term proprietary endeavors, such as IBM Watson, as embarrassing exemplars of state-of-art gaps in medical information mining, interpretation, and integrity [42-48] – lessons that drive future best Earth- and space-medicine practices and policies.

2. Learning from Trends in Robotic and Virtual Clinicians for Earth and Space Medicine and Mental Health

The above noted early and continuing industry work is currently being matched in many significant ways by the AI/ML-powered Causal Relationship Inference Search Platform (CRISP) created by the NASA-funded, SETI Institute-managed Frontier Development Lab and its Astronaut Health Challenge teams, faculty, partners, and advisors/reviewers in an effort to prototype and deploy enhanced healthcare technologies and capabilities for crewed space missions and Earth's mass civilian population. Though only in its second experimental trial iteration, CRISP aims to give accurate, private out-of-distribution inferential physical disease-classification results from high throughput or brute batch-computing workloads involving big federated datasets, such as chosen open-source Facebook Research DomainBed, Medical Information Mart for Intensive Care-III, eICU Collaborative Research Database, Mouse Genome Informatics, and NASA GeneLab synthetic datasets that target astronaut health risks and biomarkers for space-induced cancer and bone disease. The platform, employing testbed mouse and human synthetic and biological datasets, still needs to validate, scale, and otherwise refine capabilities for, but not limited to: **(1)** US Food and Drug Administration (FDA) medical device classification and regulation compliance for oncomedical, osteomedical, and other purposes, **(2)** multiclassification causal discovery that accommodates physical and/or psychiatric condition morbidity and comorbidity, and **(3)** integrated, interoperable remote user/app/medical-device/database interfaces combined with more advanced data analytics/conditioning and workflow management to support real-time private **(a)** human or surrogate clinician-patient engagement using natural and technical language processing, **(b)** digital biomedical information acquisition, processing, and interpretation (e.g., for multi-omnics and -connectome data, medical imaging stacks, (semi)structured neuropsychiatric examination inventories, industry-approved physical and mental health clinical diagnostics standards, etc.), **(c)** electronic health-record entry, manipulation, transfer, and storage, **(d)** patient appointment scheduling and follow-up contacts, and for commercial healthcare needs, **(e)** patient and third-party insurer and medicare/medicaid billing.

Such limitations in medical theragnostics, data processing, and patient-services delivery may be partially rectified by advancing virtual and embodied technologies already available in the healthcare free-/shareware and profitware marketspaces. For example, besides mainstream Google Health Assistant, Amazon Care Alexa, and Apple Siri, CRISP may be architectured to adapt human-like interactive features from inter-/intranet-interfaced personable virtual digibots developed and released for mobile neuropsychiatric evaluation and treatment in civilian patient populations. These technologies, including Tess, Sara, Wysa, Woebot, and other affordable, accessible virtual devices [49-57], assume friendly professional chatbot or Avatar personas, attempting to help patients recognize and understand their cognitive-emotional states and to learn better depression-, anxiety-, and psychoses-coping skills. Studies demonstrate that virtual digibots achieve positive patient outcomes sometimes comparable to those of actual human clinicians, even for patients suffering from severe therapy-resistant schizophrenia. Artificial surrogate-patient engagement often relies on natural language processing that detects written or verbal expressions indicative of psychological distress [e.g., 58]. Digital markers of mental health crises then cue fast selective instructional or advisory smart-algorithm responses to guide patients through challenging experiences and contexts. Surrogate robot clinicians also produce similar results to those obtained by human and virtual counterparts [59-67], particularly for the so-called social companion bots, such as Paro, eBear, Kaspar, Nao, and RoboTherapy. Although animal-like versions of these robots, which sense and respond to abnormal patient speech and movement with dynamic dialog, may not be suitable for crewed space missions, they illustrate sound remote autonomous assistive surrogate healthcare solutions for patients expressing dysfunctional mood and affect symptoms caused by social isolation and stress similar to those associated with space-mission work and living conditions. Social robot-patient interactions may also identify and mitigate poor social etiquette and peer teamwork via education and therapeutic interventions that encourage improved patient social skills, including, for instance, articulate communication, appropriate social gaze, empathy, politeness, and patience. Thus, with addition of these sorts of intelligent surrogate clinician-user engagement and diagnostic interfaces as well as other mentioned features, CRISP may become a bonafide safe, effective robotic or virtual clinician for Earth and space theragnostic medicine applications.

3. Developing and Delivering Better Human-Like Robotic and Virtual Clinicians for Space Medicine and Mental Health

Despite the promising results of current state-of-art robotic and virtual clinicians, the capacity of these agents to attain the standards of human inference, personality, learning, and additional traits largely remains unmet. Lake et al. [16] construct an optimistic ambitious plan for innovating truer representative neural-network-inspired machine emulations of human consciousness and cognition, elusive pinnacle goals of many cognitive, semiotic, and cybernetic scientists [11,12, 24,31,33,36,48,68]. Their machine-learning-based agenda, possibly requiring future generations of pioneering hybrid neuromorphic computing architectures and other sorts of technologies to be fully attained [30,32,35,36,69,70], relies on implementing sets of data-/theory-established “core ingredients” typical of natural human intelligence and development [21,36,38]. Such core ingredients, including 1) intuitive (inferential) causal physics and psychology, 2) compositionality and meta-learning (or learning-to-learn), and 3) fast efficient real-time gradient-descent deep learning and thinking, will certainly endow contemporary state-of-art machines with greater human-like cognitive qualities. But, in Lake et al.’s efforts to create a standard of human-like machine learning and thinking, they erect barriers to realizing ideal human simulation by ignoring what is also very human – variations in cognitive-emotional neural network structure and function capable of giving rise to nonnormative (or unique) personalities and, therefore, dynamic expression of human intelligences and identities [11,12]. Moreover, this same counterintuitive problem in the authors’ otherwise rational approach dangerously leaves unaddressed the major ethical and security issues of “free-willed” personified artificial sentient agents often popularized by fantasists and futurists [11,12,22,25,71], creating dilemmas for implementing artificial surrogate clinicians. To completely simulate the range of human intelligence and maximize artificial surrogate capabilities, particularly sociable and selfless tendencies critical for nascent beneficial social-like surrogate-human and surrogate-surrogate interactions, scientists and technologists must account for and better understand personality trait formation and development in autonomous artificial technologies [11,12]. These kinds of undertakings over the next decade will help yield desirable insights into the evolution of technology-augmented human existence and, perhaps more importantly, will inform best practices when establishing advisable failsafe contingencies against unwanted serendipitous or designed human-like robot or virtual clinician behavior, such as inadequate or wrong patient-health assessment and treatment; slow, inequitable, and opaque patient-service provision, deviant surrogate-patient bonding and compliance; and illegitimate patient, illness, cohort, and societal objectification.

Besides their described usefulness for modeling intended artificial cognitive faculties, Lake et al.’s core ingredients provide systematic concepts and guidelines necessary to begin better approximating human-like artificial agent traits and to probe genuine ethological, ecological, and evolutionary consequences of those traits for humans, robots, and digibots in clinical settings in Earth, space, and extraterrestrial environments. Similar reported strategies for architectures, algorithms, and performance demonstrate, however, only marginal success as protocols to reach nearer cognitive-emotional humanness in trending social robot and digibot designs [cf. 11,12], emphasizing serious need for improved adaptive quasi-model-free/-based neural nets, trainable distributed cognition-emotion mapping, and artificial personality trait parameterization. The best findings from such work, although far from final reduction-to-practice, arguably involve appearance of crude or primitive artificial personalities and identities from socially learned intra-/interpersonal relationships possessing cognitive-emotional valences. Valence direction and magnitude often depend on the learner robot or digibot disposition toward response priming/contagion, social facilitation, incentive motivation, and local/stimulus enhancement of observable demonstrator behavior (e.g., human, cohort-machine, and learner-machine behavior) [11,12]. The resulting self-/world-discovery of the learner artificial agent, analogous to human phenomena acquired during early formative (neo)Piagetian cognitive-emotional periods, reciprocally shapes the potential humanness of reflexive/reflective artificial agent actions through labile interval-de-limited self-organizing traits consistent with natural human personalities, including, but not restricted to, conscientiousness, openness, emotional stability, agreeableness, and extravertsion/introversion. Even simplistic artificial cognitive-emotional profiles and personalities thus effect varying control over acquisition and lean of agent domain-general/-specific knowledge, perception and expression of flat or excessive affect, and rationality and use of causal inference and transfer learning as applied in medical theragnostic decisions. And, by favoring certain artificial personality traits, such as openness, a learner agent's active and passive pedagogical experiences may be radically directed by the quality of teacher-student rapport [e.g., 11,12,36] and surrogate clinician-patient rapport, enabling opportunities for superior nurturing and growth of distinctive well-adjusted thoughtful agent behavior while, in part, restricting harmful agent behavior caused by impoverished learning environments. Under such constraints, an artificial surrogate clinician may learn to learn to be a safer, more effective therapist. These considerations, along with the merits of Lake et al's core ingredients, will bear increasing technical and sociocultural relevance as the Human Brain Project, the Blue Brain Project, and related connectome endeavors continue to drive imminent neuromorphic hardware research and development toward precise mimicry of configurable/computational soft-matter variations in human nervous systems and, therefore, more human-like artificial agents [cf. 72], including surrogate robotic and virtual Earth- and space-medicine clinicians over the decadal period.

4, Final Comments involving Medical Ethics

Focused, dedicated industry, academia, and government research and development will greatly advance these emerging technologies and their clinical translation over the next ten years. Suitable government and industry regulation of technology safety, efficacy, privacy, and security must keep pace with that future. Rigorous transparent discussion about proper technology-assisted medical information management and use are essential to the smooth, high-quality delivery of intelligent artificial surrogate clinicians for both Earth- and space-medicine purposes. Such large-scale coordinated community efforts facilitate cultural understanding about the medical and economic value and the societal role of intelligent technologies, encouraging and sustaining consumer confidence and positive relations between patients and healthcare-resources and -services providers. To that end, clearer guidelines [11-18,40,41,71] need to be constructed to determine whether and what artificially intelligent surrogate-clinician technologies should be subject to standard healthcare technology regulatory evaluation and approval, including provisions for (1) technology use outside the supervision of healthcare professionals, (2) professional organization recommendations and establishment of best policies and practices for training healthcare providers for technology use in different healthcare models, (3) satisfying duties of care, reporting of harm, and issuing reliable pathways for risk assessment and services referral, (4) technology oversight and services transparency which respect patient autonomy, vulnerability, manipulation, coercion, and privacy, and (6) scrutiny and mitigation of biased technology and services delivery and factors that lead to such outcomes (e.g., data validation, open source platforms for obtaining and distributing digital biomarker data, behavioral and digital phenotyping, data-driven learning engines, use of real-world evidence, cost and infrastructure for data storage and analysis, data integration with clinical records, data ownership and release, etc.).

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