Chapter 6
Mental Health Informatics

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Abstract Mental health informatics (MHI) is a relatively new specialty within the field of biomedical informatics. MHI seeks to develop, enhance, and apply informatics theories, paradigms, and technologies to optimize the mental health of individuals and communities. In this chapter we define the scope of the field and discuss its relationship not only to the larger field of biomedical and health informatics, but also to work occurring natively within the field of mental health. We introduce the three primary fields of science within which our basic scientific knowledge of mental health and illness is produced: the biological sciences, the behavioral sciences, and the social sciences. We describe the opportunities and challenges inherent in developing and using informatics technologies in a field in which knowledge is acquired in the context of three different fields in two different branches of science, each with its own unique epistemology, or way of knowing. We describe some of the unique features of the behavioral and social sciences that call for novel informatics paradigms and that highlight the need for significant enhancements in existing informatics technologies.

Keywords Mental health · Informatics · Behavioral health · Psychiatry · Psychology

6.1 Mental Health Informatics as an Informatics Subdiscipline

Mental Health Informatics (MHI) is a subdiscipline within the field of informatics. As described briefly in Chaps. 1 and 2, and exhaustively in Shortliffe and Cimino's textbook on Biomedical Informatics [1], the science of informatics is concerned

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with developing and applying theories, methods, and paradigms for transforming data into actionable knowledge to improve human health [1–3]. Informatics is inherently interdisciplinary, drawing upon theories and methods from many fields, including computer science, statistics, cognitive science, and information technology. Informatics integrates theories of human knowledge acquisition and the paradigms and technologies developed organically with the field of informatics with the theories, paradigms and technologies natively developed within the scientific domain to which it is applied. Just as bioinformatics builds on technologies developed natively within the field of molecular biology for detecting, defining, and measuring molecular entities and processes, MHI builds on technologies developed natively within the behavioral and social sciences for detecting, defining, and measuring mental and behavioral phenomena.

Mental health informatics is unique among health informatics specialties in that it seeks to acquire and integrate knowledge across all levels of the biopsychosocial model of health [4] (Fig. 6.1) with the goal of elucidating the complex interconnections between biological, mental, interpersonal, and socio-environmental phenomena. In other words, mental health informatics addresses the entire spectrum of functional systems, from physiological systems, such as the nervous system, immune system, digestive system, to those functional systems studied primarily by behavioral and social scientists such as the mind (emotion, cognition), behavior, and human communities. The entities and phenomena of interest and a few examples, are enumerated in Table 6.1.

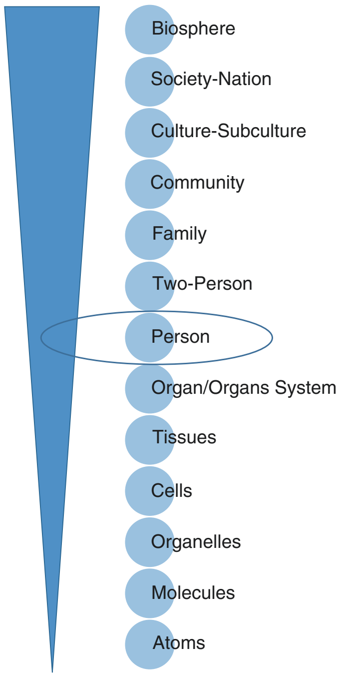

Fig. 6.1 Engel's biopsychosocial model of health. Adapted from [4]

Table 6.1 Phenomena of interest in mental health informatics

Level of analysis	Primary phenomena of interest	Constructs commonly referenced in the scientific literature
Body The anatomic entities and physiologic processes comprising the entire human body • The biological part of Engel's "Person" level and all levels below it [4] • The *genes*, *molecules*, *cells*, *circuits*, and *physiology* units of analysis defined in the National Institute of Mental Health's Research Domain Criteria (RDoC) framework [5, 6]	Mental health informatics is particularly concerned with physiologic processes that influence one's own or another's brain, e.g., how the microbiome of a person's digestive system influences his or her brain, or how pheromones produced by one person influence the brain of another person.	Anatomic entities and processes comprising physiological systems, including (but not limited to) the: • Nervous system • Endocrine system • Immune system • Integumentary system • Digestive system The molecules (including genes), cells, circuits, and physiological phenomena defined in the RDoC framework [5, 6].
Person The body, mind, and behavior of a single human being • The psychological (mental, cognitive, behavioral) part of Engel's "Person" level of analysis • The *behavior* and *self-report* units of analysis defined in RDoC [5, 6]	The phenomenological experiences, and mental and cognitive functions occurring *within* a single person. The behaviors—ranging from simple motor behavior to complex social behavior—that an individual selects and executes. The attributes of the relevant contexts in which each of these phenomena occur, and the relationship *between* these "intrapersonal" phenomena and the context.	Mind • Mental functions, e.g., consciousness [7–11], motivation and drive [12–18], emotion [19–24], and sensation [25] • Cognitive functions [5, 26–28], e.g., perception [5, 25, 29–31], memory [5, 32], attention [33–36], thinking [37, 38], learning [39–41], language [42], reasoning [43–47] • The component and integrative functions that comprise the "gestalt" construct mind [48–51] Self • Agentic self [52–54] • Objective self [5, 55], self-concept [56–61], self-efficacy [62], self-esteem [57, 63] • Personality [64–68], identity [69–71], moral development [72–74] Behavior • Affect (expression of emotion) [75, 76] • Posture, motor behavior, and symbolic communication [5, 77, 78] • Complex social behavior [39, 79–81]

(continued)

Table 6.1 (continued)

Level of analysis	Primary phenomena of interest	Constructs commonly referenced in the scientific literature
Dyad Two people co-located in the same space and time, interacting in ways that range from nothing more than awareness of co-location to ongoing and extensive interaction. • Engel's "Two-Person" level [4]	The novel physiological and behavioral phenomena that emerge *between* two people when they interact and the unique physiological, mental, and behavioral phenomena that emerge *within* each person as a participant in in a dyad. The attributes of both the dyad, e.g., nature of relationship, and the individual people, e.g., social class, gender, personality traits, that influence these phenomena.	Types of Dyads • Parent-child relationships [82] • Close [83–86] and romantic [87] relationships Interpersonal functions and processes • The component and integrative functions comprising the "gestalt" of interpersonal process [84, 88] • Attachment [5, 89–93]
Group Three or more people co-located in the same space and time, interacting in ways that range from nothing more than awareness of co-location to ongoing and extensive interaction. • Engel's "Two-Person" level [4]	The novel physiological and behavioral phenomena that emerge *between* people when they interact in groups of three or more, as well as the unique physiological, mental, and behavioral phenomena that emerge *within* each person (and each dyad) in this context. The attributes of the group, the component dyads, and the individual people that influence these phenomena.	Types of Groups • The Family [94, 95] • Community and tribe [96–98] Group functions and process [99–104] • Affiliation [5, 105–107] • Alliance formation [108–110] • Social dentification [103, 111–114] • Competition, cooperation, and compliance [115–117] • Dominance hierarchies [118, 119]
Society, Culture A group of people co-located in the same sociocultural and geospatial context (a peer group, organization, neighborhood, community, country, world), interacting in ways that range from simple temporal co-location to extensive interaction.	The novel physiological and behavioral phenomena that emerge *between* people when they interact in some larger sociocultural and geospatial context, as well as the unique physiological, mental, and behavioral phenomena that emerge *within* each subgroup and person in this context. The attributes of the group, subgroups, and individual people that influence these phenomena.	Types of cultures and social communities: • Organizational (educational, employment, or living environment-based) and peer cultures [120–122] • Geographic, political, religious, racial, ethnic groups and cultures [123, 124] Social functions and processes: • Social structuralism [125] and social agency [126] • Social norms [117, 127] • Social cognition [128–130] and social identification [103, 111–114] • Acculturation [124, 131]

Table 6.1 (continued)

Level of analysis	Primary phenomena of interest	Constructs commonly referenced in the scientific literature
Physical Environments The biological and non-biological entities and processes within a defined geospatial context	The novel phenomena that emerge *between* and *within* people in the context of specific physical environments. The novel phenomena that arise within the physical environment when people spend time in the environment (with an emphasis on phenomena that in turn impact human mental health). The attributes of the environments and the people that influence these phenomena.	Types • Spaces, buildings, neighborhoods, larger ecological environments Phenomena • Amount and configuration of space [132–135] • Light [136–138], noise [139, 140] other sensory stimuli in the environment

6.2 Contrasting Mental Health Informatics with Related Disciplines

The field of MHI overlaps significantly both with mainstream informatics specialties and with work being done in several mental health specialties. In this section we focus on the ways in which MHI is similar to, and differs from, mainstream biomedical and health informatics. We go on to describe how MHI aligns with, and builds upon, informatics paradigms being developed and use natively within mental health disciplines, as well as how it differs. We end this section by providing a brief overview the ways in which mainstream biomedical and health informatics has addressed mental, behavioral and social phenomena.

6.2.1 How Mental Health Informatics Differs from Mainstream Biomedical and Health Informatics

While there is significant overlap between MHI and other informatics specialties, there are several things that make MHI unique. First, MHI deals with phenomena not typically encountered by informaticians working in other domains of health. Second, because the phenomena of interest in mental health are fundamentally different from those of interest in medicine, the paradigms used to isolate, define, and quantify them are also different. Consequently, there are important differences in how we approach the core informatics knowledge acquisition cycle in MHI compared to mainstream health informatics.

6.2.1.1 Differences in the Phenomena of Interest

Mental and psychological phenomena (the “mind” and “self”) as well as interpersonal, social, and cultural phenomena, all play a central role not only in theories of mental health and illness, but also in interventions designed to optimize health and treat illness. This is not to say that these phenomena are not relevant in mainstream theories of physical health. Rather, they are generally not part of the core epistemology (see definition in Table 6.2) of the biological sciences upon which knowledge of physical health and illness is based.

Because the phenomena of interest in mental health are fundamentally different kinds of things from the phenomena of interest in physical healthcare, there are fundamental differences in the way these phenomena are named, defined, and quantified. Compared to physiologic phenomena, such as temperature, blood pressure, or weight, “psychological” phenomena such as level of introversion, depth of sadness, ability to detect social cues, and cognitive capacities are much more difficult to clearly define, isolate, sample, and quantify. Interpersonal phenomena, such as quality of attachment, manifestations of racial contempt, or level of interpersonal

Table 6.2 Key terms defined

Brain	The physical organ inside the skull that controls and coordinates physical, mental and behavioral functions.
Mind	The conceptual entity used to describe entities, functions, processes, and states underlying observable physical and phenomena being attributed to something occurring in the brain. For example, memory is typically described in terms of things that happen in the mind (v. the brain), such as 'storing', 'retrieving', and 'representing' information. Phenomena that cannot be fully and explicitly defined in terms of biological entities or processes in the brain are typically defined in terms of entities or processes attributed to the mind.
Biological sciences	The science concerned with the study of living organisms.
Behavioral sciences	The science concerned with the study of human and animal behavior.
Social sciences	The science concerned with the study of groups and social relationships.
Epistemology	The field of philosophy concerned with the study of human knowledge. In the context of a specific scientific discipline, the field's "epistemology" is the set of theories, paradigms, and methodologies the field uses to determine what constitutes valid knowledge (sometimes defined as "justified, true belief") [141–145].
Construct	A real-world thing that has no tangible manifestation in the physical world, but rather, is inferred on the basis of other observations. For example, 'memory' is a construct, because we can't directly observe memory, we can only infer its existence based on observations (i.e., we can recall the name of a person we met last week) along with theories about observations (there is some 'thing' called memory within the brain that captures and saves information about people we meet, when we see the person again, we can pull information back out of this 'thing'). The existence of—and accuracy of any definition of—the construct can only be assessed in the context of both the observations and the associated theory [146].
Mental phenomena	Functions, processes, and states that can be *fully* defined only by referring to entities or processes attributed to the mind, rather than to entities or processes attributes to the body (brain). Examples include one's visual perception of an image or auditory perception of a song; a thought, a belief, or an attitude; an emotion, a memory, or an intuition; reasoning, planning, comprehending, and calculating.
Psychological phenomena	A commonly used, but poorly defined term. The American Psychological Association (APA) defines psychological phenomena as including "all aspects of the human experience—from the functions of the brain to the actions of nations" [147]. To the APA, psychological phenomena are the superset of functions, processes, and states that comprise human existence—biological, mental, behavioral, interpersonal, social, and cultural. Many behavioral scientists and clinicians, including psychologists, use the term "psychological" more narrowly to refer to the things that occur within an person's mind.
Behavior	We defined behavior here as observable physical activities ranging from simple physical and motor behavior to complex interpersonal and social behavior. The term is sometimes used to more broadly to refer to any function, process, or state that can be objectively observed or measured [147].

(continued)

Table 6.2 (continued)

Social phenomena	The entities (e.g., dyads, groups, organization structures, social norms, laws, etc.) and processes that emerge when two or more people co-exist or interact in the same place and time [148].
Psychometrics	The field of study concerned with measurement of psychological phenomena (defined in the broad sense of the term). It includes the set of theories, paradigms, instruments, and quantitative methods used to identify and define latent (underlying, unobservable) constructs based on samples of observable behavior [147].

respect between members of a family, team, or community are equally difficult to clearly define, isolate, sample, and quantify. Consequently, in mental health, there is less consistency in the naming of major clinical concepts, and less consensus about their explicit definitions and relationships to other concepts. For example, the terms "mental model" [149], "schema" [150], and "working model" [151] are used by various researchers and clinicians to describe the mental representation a person has of some person, situation, or event. While there is some overlap in the definition of these terms, the theoretical model in which each construct is defined posits nuanced differences between the construct and its relationships to other constructs. There are also different paradigms and methods (including instruments) used to measure this construct in both research and practice, with different paradigms and methods developed and used by those belonging to each theoretical camp in which the construct is articulated.

This is different from physical health where major concepts such as blood pressure, inflammation, and platelet count are named and defined the same way across the entire field. There is general consensus among health professionals not only about the definitions of, but also about optimal methods for measuring, each of these things. In contrast to mental health, the definitions and methods do not vary based on the school the healthcare professional attended, the institution where she or he trained, or whether she or he specialized in oncology, cardiology, or pediatrics. Moreover, there is widespread consensus about the relationship each of these entities or processes has to other biomedical entities and processes.

In traditional biomedicine, then, the instruments and methods used to measure most biomedical phenomena are universal and readily available, and the same kinds of instruments used in research are used in routine healthcare. This is not the case in mental healthcare. In mental healthcare, while formal methods and instruments for measuring clinical phenomena are used in research paradigms, these instruments are rarely used in routine clinical practice. For example, with the exception of a few instruments, such as the PHQ-9, the standardized assessment and imaging technologies used in research are rarely used in practice. Moreover, while increasingly sophisticated and reliable technologies that allow researchers and clinicians to visualize, measure, and quantify biological entities and processes are continuously developed and widely disseminated, most of the instruments and methods currently in use in physical healthcare have been vetted over a long period of time. The data generated using these instruments and methods are assumed to be valid and reliable representations of the phenomena of interest. A neutrophil count generated by a CBC machine in one part of the world in 1980 is assumed to be comparable to a neutrophil count generated by a CBC machined in another part of the world in 2020. A measure of the existence or severity of depression generated by the available version of the Beck Depression Inventory (BDI) in 1980 (the BDI-I [152]) however, may not be comparable to a measure of the existence or severity of depression generated based on a clinical interview, another depression assessment, or even based on the version of the Beck Depression Inventory available in 2020 (BDI-II [153]).

This consistency in terminology, operational definitions, and instrumentation makes it possible to perform meta-analyzes of research findings and to pool and analyze clinical data across researchers and clinicians. In mental health, on the other hand, the inconsistency in terminology, the variation in operational definitions of core constructs, and the variety of instrumentation makes it difficult to pool data or perform meta-analyzes across theoretical and philosophical boundaries.

6.2.1.2 Differences in the Knowledge Acquisition Cycle

The aspiring mental health informatician will need to be aware that the unique types of phenomena of interest in mental health—and the many challenges inherent in unambiguously defining and quantifying them—create a different kind of relationship between the *data* an informatician has to work with and the underlying real-world "thing" the data represents. Despite the widespread existence of empirically validated methods and instruments for measuring the behaviors, internal experiences, and interpersonal and social phenomena relevant to mental health, not all instruments that purport to measure the same underlying construct, e.g., impulsivity, introversion, racism, etc., are actually measuring precisely the same thing [154]. Unlike in physical healthcare, where we can be relatively confident that two tests claiming to measure some biological entity—say, antibodies to COVID19—are fact measuring the same thing, i.e., one test is not measuring, for example, a mix of COVID19 and Flu antibodies, we cannot always be certain that two validated instruments claiming to measure the same psychological construct—say, impulsivity—are in fact measuring the same thing. Observations ("data") about the phenomena of interest in mental health are much more sensitive to the paradigms and instruments used to sample and measure them than are the biological phenomena commonly measured in physical health. Moreover, each paradigm and instrument may actually be measuring different aspects of the same construct, or completely different constructs altogether [154–156]. Consequently, data about mental, social, and behavioral phenomena must be accompanied by much more data about the context of measurement in order to be useful in knowledge acquisition paradigms. Moreover, in routine mental healthcare, the method used as the basis for a clinical observation is often not explicitly captured with the data, and in those cases, it is important for the informatician to understand that gaps in context may imply a method was "clinical impression' and the instrument used was "none". This distinction between observation and context of observation that is not typically made in medical informatics paradigms—probably because it is tacitly accepted as “redundant”—must be explicitly acknowledged in mental health informatics paradigms.

As described in Chap. 2, data are the primary inputs to the *data to information to knowledge to action cycle (*the “DIKA Cycle”) that defines informatics. Implied in the data acquisition step is a “signal to data” step, where the observable signals generated by the real-world phenomena are captured, quantified, and represented as “data” (Fig. 6.2) from which information can be generated and knowledge subsequently acquired.

This “signal to data” step (Fig. 6.3) presents a challenge to many informaticians working in mental health because the paradigms, methods and instruments used to isolate, acquire, and quantify these mental, behavioral, and social “signals” differ

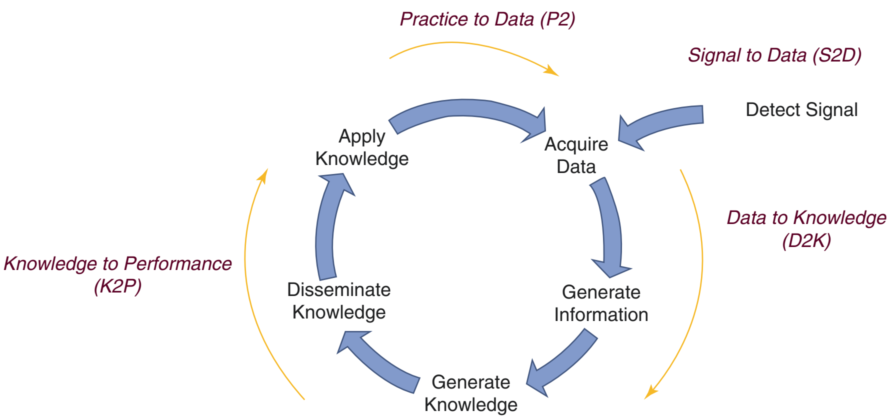

Fig. 6.2 The core *data to information to knowledge to action* (DIKA) cycle with an emphasis on the prerequisite process of detecting and quantifying observable signals of the phenomena of interest

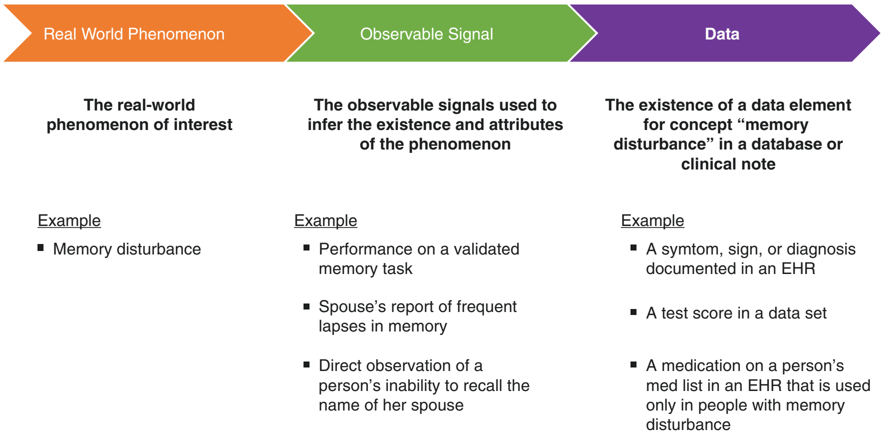

Fig. 6.3 Data as representations of the observable signals used to infer the existence of some real-world phenomenon

significantly from those used to acquire basic knowledge about physiological phenomena (see Chap. 9). Similarly, the instruments and methods used in clinical practice to detect, diagnose, prevent, and treat mental health conditions differ in important ways from those used in traditional medical practice. While they may not provide the same certainty of insight into, and comparability of results about, the phenomena they measure as the medical instruments we, as informaticians, have come to know and trust, they are, nonetheless, developed using robust scientific methods that have been empirically demonstrated to produce high quality representations of the phenomena they seek to measure. In fact, there is an entire subspecialty in the behavioral and social sciences dedicated to developing these measurement technologies. This is the science of *psychometrics*, described in detail in Chap. 9. Here, we simply point out that there is a fundamental difference between mental and physical health in how the raw "signals" underlying the phenomena of interest are detected and measured, and how these signals become "data" in the knowledge acquisition (DIKA) lifecycle. Because most experienced informaticians tend to have far less knowledge about, and experience with, psychometric theory and methods than they do with the biological theories and methods, this is an important domain of study for any aspiring mental health informatician.

While many of the methods and paradigms used to derive meaningful information and knowledge from physiologic observations can be applied to mental, behavioral, and social observations and data, many methods are specific to the phenomena being observed. Chapters 10, 13, and 14 describe informatics methods that can be applied universally across virtually all types of observable phenomena, given that the phenomena in question are accurately represented and quantified. These methods include computational and analytic methods (Chap. 10), natural language processing (NLP) methods (Chap. 13), and data visualization methods (Chap. 14). Chapters 9 and 12 describe methods used to derive actionable knowledge from data points representing signals derived from fundamentally different types of phenomena. While Chaps. 8 and 11 describe methods for knowledge acquisition given data points representing physiologic signals, Chap. 12 describes methods for knowledge acquisition given data points representing mental, behavioral, and social signals.

In addition to differences between the scientific paradigms used to derive knowledge about mental versus physical health, there are also significant differences in the overall landscape of theories of pathology and approaches to treatment used in mental versus physical health. As described in Chaps. 3, 9, and 12, there are many widely accepted—sometimes contradictory—theories of the mechanism underlying not only mental illness but also normative psychological development. This plethora of etiological theories of psychopathology, combined with the number of different clinical treatment models (even for a single, shared etiological conceptualization of one disorder) is common in mental healthcare, yet far less frequently seen in biomedical healthcare. This creates an added layer of complexity to the information and knowledge acquisition process. Specifically, the aspiring mental health informatician will need to build multiple models—each one incorporating assumptions from each of the multiple theoretical models of pathology—into the paradigms and methods used in the initial processing of the data, and find a way to integrate these models as she or he applies analytic methods to derive information and knowledge from raw data.

6.2.1.3 How Mental Health Informatics Differs from Other Informatics Work in Mental Health

Mental health informatics differs not only from traditional health informatics, but also from other informatics subdisciplines working to explicitly address mental health and illness, such as computational psychiatry, neuroinformatics, and behavioral health informatics. In the past several years, an increasing body of work [157–163] has begun to emerge describing informatics efforts applied to mental health. These works demonstrate how researchers in the basic behavioral sciences are applying informatics methods to better understand phenomena related to the brain, mind, and behavior. They also demonstrate how clinicians and healthcare administrators are addressing the use of informatics technologies to improve care delivery and accelerate the rate of knowledge acquisition based on data captured during the routine delivery of care. These efforts—and the similarities and differences between them—are described in Table 6.3.

Table 6.3 Informatics applied to mental and behavioral health

Terms	Primary phenomena of interest[a]	Objective
Neuroinformatics	The structure and function of nervous system molecules, cells and tissue, and neural circuits.	Improve physical and mental health by building a robust informatics infrastructure to support the acquisition and dissemination of knowledge required to optimize the structure and function of the nervous system [157, 160, 162].
Computational psychiatry	Mental functions, processes, and states and their relationships the brain functions, processes, and states.	Improve mental health by building an integrated scientific and clinical infrastructure capable of acquiring and applying knowledge required to optimize mental and behavioral functions and processes [163, 164].
Behavioral health informatics, mental health informatics	The development and application and development of computer-based technologies to support knowledge acquisition and delivery of mental healthcare.	Improve mental health by optimizing the scientific and clinical workflows used to prevent and treat mental, behavioral, interpersonal, and social dysfunction [165, 166]
Mental health informatics (as defined in this text)	The complex interactions between mental, behavioral, interpersonal, social, and environmental entities, functions, processes, and states, and the informatics paradigms	Improve mental health by building a robust LHS capable of acquiring, disseminating, and skillfully applying precision knowledge to prevent and treat mental, behavioral, interpersonal, and social dysfunction.

[a]Primary phenomena are those that appear to be the focus of research and implementation paradigms; that is, while other phenomena may be studied in relation to one or more of the primary phenomena of interest, it appears to be primarily with the goal of understanding their relationship to the primary phenomena

6.2.2 Mental, Behavioral, and Social Phenomena in Mainstream Health Informatics

While mainstream medicine has traditionally focused primarily on physiological phenomena, it is increasingly recognizing the intricate relationships between mind and body, as well as the significant role that social and physical environments play in overall health. Moreover, both researchers and clinicians are increasingly emphasizing the role of non-physiological variables in physiologic health and illness. This shift in emphasis to an integrated, whole-person approach to health is clearly reflected in developments in the field of informatics. In the past several years, there have been many studies describing the application of informatics technologies not only to research on mental health conditions [165, 167, 168], but also more generally to the mental, behavioral, social, cultural, and environmental aspects of human health [169–171].

Researchers in bioinformatics have performed genome-wide association studies (GWAS) for many mental health conditions in an effort to learn more about the genetic basis of these conditions [172–175]. They have studied the genetic basis of various anatomic and physiologic phenotypes associated with mental health conditions [176–178] and to a lesser extent, the genetic basis of behavioral phenotypes associated with the same [179]. Researchers in pharmacogenomics have moved this basic bioinformatics research down the translational spectrum by performing clinical research to address the problem of predicting which psychiatric pharmacotherapies are most likely to work for which people [180]. Applied clinical informaticians have moved this knowledge even further down the translational spectrum by implementing clinical guidelines for pharmacogenomics testing as clinical decision support for prescribing behavior by front-line clinicians [181, 182]. These and many other examples of the use of bioinformatics research paradigms for knowledge discovery in mental health are described in Chap. 11. Researchers in neuroinformatics have made similar strides in understanding not only the structural and biochemical underpinnings of behavioral phenomena and common mental health syndromes, but also the neurocircuitry [157, 160, 162] underlying the same. Examples of the application neuroinformatics paradigms for knowledge discovery in mental health are described in Chap. 8.

There has also been progress in the development of an important, foundation set of informatics technologies: technologies for concept and knowledge representation which underpin all other informatics technologies (Chap. 7). As the use of electronic health records (EHRs) and other clinical information systems in mental health has increased, there has been increasing demand for robust clinical terminologies that can be used to unambiguously represent clinical observations in mental health research and care. In 2010, for example, the Logical Observations Indentifiers Names and Codes (LOINC) [183] terminology created a way to define and code structured assessment instruments to support the explicit representation of data captured using psychological assessment instruments [184, 185]. Similarly, in

2018, under the auspices of SNOMED International, the Mental and Behavioural Health Clinical Reference Group (MABH-CRG) was established to evaluate and address gaps in SNOMED-CT (the Systematized Nomenclature of Medicine—Clinical Terms [186]) relative to mental health. These activities reflect an urgency to address gaps in frameworks and standard terminologies relative to mental health [187–189] in an era of increasing policy pressure for interoperability of health data [190–192].

Informaticians in collaboration with mental health researchers and practitioners have addressed the need for more robust informatics technologies for mental health at virtually all points in the research and care delivery process (Chap. 5). For example, many technologies have been developed for signal detection at a physiologic (e.g., heart rate and oxygen uptake) [193, 194], mental (e.g. detection of depressive symptoms) [195–197], phenomenological (e.g., sleep) [198], and behavioral level (e.g., Ecological Momentary Assessment, promotion of physical activity and weight loss) [199–201]. These technologies are discussed in detail in Chap. 9. The research framework constructs and subconstructs put forth by the National Institute of Mental Health's (NIMH) Research Domain Criteria (RDoC) [5, 6], including mental, behavioral, and social constructs have also become the focus of much informatics activity [202, 203] (Chaps. 7, 12, and 23).

Biomedical informatics has also addressed mental and behavioral phenomena in work on important topics such as computer-human interaction (HCI) and implementation science. In these cases, the mental and behavioral phenomena of interest are as like to be those occurring within the healthcare practitioner as those occurring within the healthcare recipient (e.g., how a healthcare practitioner processes information presented in various ways in a clinical information system). Electronic health record systems (EHRs) have been one particular area of interest in HCI [204]. A significant body of work takes HCI one step further into the mental/cognitive domain in an interdisciplinary subdomain known as cognitive informatics, which focuses on human information processing [205]. In addition, health information technologies may be deployed at home after patient discharge, emphasizing an entirely different area of study in human factors [206].

6.3 Mental Health Informatics: Bridging the Biological, Behavioral, and Social Sciences

Our current scientific knowledge about mental health and illness comes from two distinct branches of science: the social and behavioral sciences on the one hand, and the biological sciences on the other. In the social and behavioral sciences, in fields such as sociology, psychology, and cognitive science, a diverse range of mental, interpersonal, social, and cultural phenomena play a central role in theories of mental and behavioral functioning. In the biological sciences, in fields such as psychiatry and neuroscience, physiological systems such as the nervous system, endocrine system, and immune system take center stage in theories of mental and behavioral functioning.

Consequently, MHI must be able to accommodate the theories, paradigms, and methods of multiple, distinct branches of science. This is challenging for a number reasons. The first is that traditional biomedical informatics is ill-equipped to handle the kinds of mental, behavioral and social phenomena that dominate theories and clinical models in mental health. The second is that profound differences in epistemology, or "ways of knowing" between the behavioral and biological sciences create obstacles to collaboration between informaticians and behavioral and social scientists. Lastly, the vast number of competing, and often contradictory theories within the behavioral and social sciences [189] places unique demands on informaticians (or indeed any reseachers) working in the domain.

6.3.1 Mainstream Health Informatics Has Not Fully Embraced Social and Behavioral Phenomena

Because health informatics has its historical roots in the biological sciences, many of the informatics technologies required to address social and behavioral phenomena are not part of the standard informatician's toolkit. Moreover, the informatics technologies developed over the first several decades of the field's existence have been developed and optimized for acquiring and applying knowledge about physiological, rather than mental, behavioral, or social phenomena. Consequently, many of these technologies are not well suited for use in mental health informatics paradigms. Let's take a look at how these historical blinders impact the work of the mental health informatician at each stage in the knowledge acquision process.

As previously discussed, all informatics paradigms consist of the same core goal of acquiring actionable knowledge from data about some underlying health-related entity or process. The same core steps occur in all informatics paradigms. First, the relevant underying real-world entities and processes of interest are identifed. Next, the observable signals produced by these entities and processes are captured and quantified (measured). Third, these observed signals are described in the form of "data" that can be manipulated both by the human brain and computer based system. Fourth, these data are transformed into information. Next, the information is transformed into actionable knowledge. Finally, as the ultimate goal, actions are taken to implement the aquired knowledge into research and clinical workflows to improve human health (Fig. 6.4).

Fig. 6.4 Informatics technologies are developed and applied for each of several core steps in the knowledge acquision process

Differences between paradigms for signal detection and data catpure in the biomedical versus the social and behavioral sciences were discussed in the previous section, and are described in more detail in Chap. 9. The process by which both the real world phenomena of interest in healthcare and the observable signals used to isolate, identify and measure them are transformed into data is described in informatics as "concept and knowledge representation" [89, 187, 188] and is discussed in detail in Chap. 7. Because data is the foundational input to all informatics paradigms and methods, there is arguably no area of informatics that is most critical to enabling an LHS for mental health than ensuring that technologies for concept and knowledge reqpresentation are both adequate for representing mental health content, and fully cover the domain.

Two clinical terminologies essential to a building an LHS in mental health health—Logical Observation Identifiers Names and Codes (LOINC) and the Systematized Nomenclature of Medicine-Clinical Terms (SNOMED CT)—not only have significant gaps in content relative to mental and behavioral health [187, 188], but are also designed in such a way that they cannot capture the meaning of concepts relevant to mental health as completely as they represent the meaning of concepts relevant to biomedical health. This is because the terminologies themselves have been designed based on assumptions inherent in the biological sciences. An unpublished evaluation of the attributes used to define clinical finding concepts in SNOMED-CT, for example, revealed an implicit assumption that the universe of health findings and diseases can be fully defined in terms of physical, biological, and morphological entities. This is evidenced by a conceptual world view that defines clinical findings in terms of the functional systems, body structures, morphological alterations, and processes involved, and that restricts the range of functional systems and processes to those outside of mental, interpersonal, or social systems (See Chap. 7). Similarly, MeSH (Medical Subject Headings), the terminology used to index publications in PubMed, contains far fewer, and far less detailed, index terms for retrieving research about mental, behavioral, and social phenomena, diseases, and treatments, than for retrieving research about biological phenomena, diseases, and treatments [188]. Where terminologies do exist with a detailed and accurate representation of mental, behavioral, and social phenomena, they tend to have been developed natively within the behavioral sciences, without the benefit of informatics best practices for terminology development [87]. Moreover, these terminology products are less likely to be included in systems that manage and publish inventories of national industry standards (see Chap. 7).

Knowledge dissemination is another part of the process not well addressed by traditional informatics technologies in the context of mental health. Knowledge dissemination is a critical step in moving from knowledge to action. Methods for biomedical knowledge dissemination include those commonly used in medical schools and medical healthcare settings, as well as those used by medical boards and medical professional societies. Examples include publishing clinical guidelines, implementing those guidelines through order sets in EHRs, ongoing continuing education and maintenance of certification requirements, and other forms of education including journal articles and professional conferences. Knowledge dissemination in mental health is more complex, primarily because of the number and variety of educational programs and settings, as well as professional boards and societies.

As discussed in Chap. 4, there are several times as many psychologists as psychiatrists in the United States, in addition to the ranks of case workers, social workers, etc. As a result, primary dissemination is not through a small, relatively homogenous group of medical schools, settings, boards, and societies, but rather through a complex system of training and licensure programs. Moreover, complete knowledge about mental health is often shared across scientific and disciplinary boundaries. Physicians and advanced practice nurses typically do not have the same depth of psychological, behavioral, and social science training that mental health professionals trained in the behavioral and social sciences do. Similarly, mental health practitioners trained in the behavioral sciences typically do not have the same depth of biomedical training that physicians and advanced practice nurses do. Each group has limited insight into not only the complete knowledge base, but also the theoretical models and knowledge discovery paradigms of the other. Consequently, neither group is fully equipped to integrate relevant knowledge from the discipline in which they were not trained.

In addition, mental healthcare is often delivered in a small or solo practice setting rather than in a hospital or large clinic setting. These smaller settings are less likely to have deployed EHRs than hospitals and clinical settings providing biomedical healthcare services (see Chap. 16). While there has been a significant uptick in EHR adoption since the HITECH Act in 2009 due to financial incentives for demonstrating "meaningful use" of electronic systems [207], due to the initial exclusion of mental health providers from these incentive programs, EHR adoption in mental health has lagged behind [208]. Thus, knowledge dissemination through EHR-enabled clinical decision support is not feasible in many common mental health care settings.

6.3.2 Epistemological Differences Between the Behavioral and Biological Sciences

Arguably the biggest challenge facing informaticians working in mental health informatics is that the biological, behavioral, and social sciences are based on profoundly different assumptions about the nature and relevance of mental, behavioral, social, and biological phenomena in health and illness. In addition, the biological and behavioral sciences differ in the scope of phenomena about which they believe knowledge can be legitimately acquired. In the biological sciences, the scope is physical phenomena that can—at least theoretically—be directly observed. The behavioral and social sciences, on the other hand, focus on phenomena that cannot be directly observed, such as thoughts, emotion, and social norms. As a result of differences in objects of study, the biological and behavioral sciences have different ideas about the methods by which they believe the objects of scientific study can be

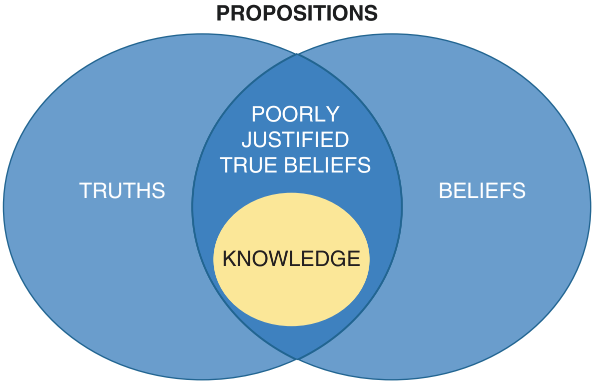

Fig. 6.5 Knowledge as justified true beliefs (adapted from https://en.wikipedia.org/wiki/Epistemology)

legitimately known. In other words, the behavioral and biological sciences have fundamentally different *epistemologies* (Fig. 6.5).

The term *epistemology*, from the Greek words for 'knowledge' and 'discourse', refers to the study of the nature of human knowledge [49, 209]. As a field of study, epistemology is concerned with answering the question: "How we can legitimately claim to know something?". That is, how can we make the leap from believing something to be true, to "knowing" something to be true? When used in the context of a field of science, *epistemology* refers to the criteria a scientific field uses to determine that sufficiently valid evidence has been produced to say that a hypothesis (a belief) has achieved the status of knowledge. It refers to the rules (or criteria) the field has about what a scientist must do to justify a belief. These criteria are typically defined in terms of the paradigms, methodologies, and instruments the field believes are capable of reliably producing valid observations. A neuroscientist, for example, may say that only emotional states that can be reliably distinguished based on neural signals measured using brain imaging technologies can be known. She might say that the names we give to more nuanced emotional states measured using psychometric methods are hypothetical (beliefs), but cannot be known, because to the neuroscientist, psychometric methods and instruments are not valid methods for identifying or measuring emotional states. A field's epistemology also defines *what* can be known [144, 145]. That is, *what* classes of phenomena are capable of producing a valid, observable signal capable of detection, and what classes of phenomena can be detected using the tools and technologies available in the field. Finally, an epistemology defines *who* can be knowers [144, 145, 209]—what skills or training are required to be capable of "knowing" in the specific field. Each field develops, validates, and iteratively refines a set of tools and technologies to "come to know" the entities and phenomena the field believes can be known.

Previously, we described how the entities and phenomena of interest, as well as the methods and paradigms used to acquire actionable knowledge from these phenemena vary accross the biological, behavioral, and social sciences. Epistemology gives us a framework for thinking more systematically about the differences between the fields. Importantly, it allows us to explicity represent and proactively identify potential obstacles to knowledge acquisition in a field grounded in more than one branch of science. It also helps us operalize strategies for addressing these obstacles.

Neuroscientists tend to define mental and behavioral phenomena in terms of the brain [160, 163, 164], or an 'embodied mind' [50]. The constructs, theories, tools, and technologies they develop and use are designed to elucidate the relationship between biological (non-brain), mental, behavioral, interpersonal, social, and environmental phenomena on the one hand, and brain phenomena on the other. The empirical questions they ask are aimed at understanding ways in which both non-biological (mental, social, environmental) and biological (immune, digestive, integumentary, etc.) phenomena influence—or are influenced by—structural and physiological aspects of the brain. For example, a neuroscientist studying racial descrimination might use fMRI imaging to understand the circuitry and biological processes underlying differences in emotional responses to, and reasoning about, an injustice perpetrated upon a member of the same versus a different racial group. She or he might compare systematic differences in neural activity between a cohort of individuals who self identify as racial separatists, and those who self-identify as anti-racist.

In contrast, behavioral scientists tend to define mental and behavioral phenomena in terms of a mind, agnostic about the relationship between mental phenomena and the brain [160, 163, 164]. The constructs, theories, tools, and technologies they develop and use are designed to elucidate the relationships between and among various mental, behavioral, interpersonal, and social phenomena. Social scientists address a slightly different range of phenomena, interested primarily in relationships between individual people, groups of people, and phenomena that arise in the context of the interaction between them. Like the pure behavioral scientist, the pure social scientist is agnostic about the relationship between social phenomena and the brain. Whereas the neuroscientist described above studied racial discrimination by looking at the biological correlates of racism, a behavioral scientist is more likley to examine the relationship between internal beliefs and attitudes and emotionally charged experiences with members of the same and different racial groups. A social scientist, on the other hand, might examine the relationship between a person's attitutes towards people of a different racial group and the attitudes and behavior of peers and authority figures. Alternatively, she or he may study the relationshipo between a person's attitutes towards people of a different racial groups and the types and prevalence of various images of that racial groups in the media.

This is not to say that pure biological scientists do not 'believe in', or care about, more abstract aspects of the mind and social phenomena, or that pure behavioral and social scientists do not 'believe in', or care about, the biological basis of the mind and social phenomena. In fact, there is significant overlap between these fields and a number of interdisciplinary sciences have emerged at their intersections (Fig. 6.6).

There are fundamental epistemological challenges inherent in acquiring knowledge by integrating theories within and across each of the three branches of science most relevant to MHI. These challenges are embraced, and explicitly addressed by the NIMH's Research Domain Criteria (RDoC) framework, discussed in detail in Chap. 12. Here, we want to briefly touch on the fundamental challenge of defining the relationships between brain and behavior.

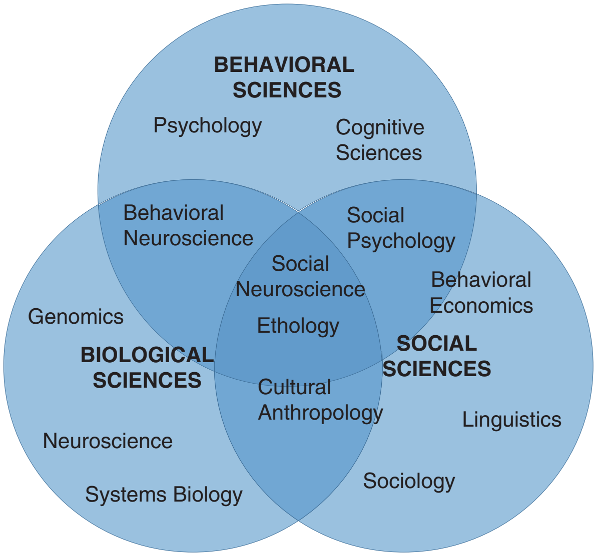

Fig. 6.6 Interdisciplinary knowledge base underlying mental healthcare

6.3.3 A Primary Epistemological Challenge for Informaticians: The Relationship Between the Mind and Brain

One of the primary challenges for informaticians working in MHI Is developing paradigms and technologies that integrate the disparate theories of mental functions and human behavior espoused by scientists working in the biological and behavioral sciences, and the often-passionate belief in the unique legitimacy of one perspective. Thanks to our more philosophically oriented colleagues in the field of Neurophilosophy (see [49]), we can operationally define the root cause of this inter-scientific conflict. Neurophilosophy tell us our conflict is not new and that this difference of opinion about the relationship between mind and brain has deep historical roots [49, 51, 209]. While a comprehensive review of the philosophical literature on the mind-brain question is beyond the scope of this book,[1] a core distinction can be made between 'monism' and 'dualism' (Table 6.4). The monist's stance is that the brain and mind are not distinct entities and that there is only one entity—the brain. Monism does not deny the existence of the mind. Rather, it views it as an epiphenomenon of brain functioning. The dualist stance is that the brain and the mind are, in fact, distinct conceptual entities. Dualism argues that the brain directly influences the mind, and the mind directly influences the brain, but that even with the most sophisticated tools and technologies, science will never be able to reliably and fully define complex mental phenomena in terms of specific physiologic brain phenomena.

[1] See *Neurophilosophy: Towards a Unified Science of the Mind/Brain* by Patricia Smith Churchland for a thorough and accessible discussion of the historical foundations of the issue.

Table 6.4 Philosophical approaches to defining the relationship between the brain and mind

Model	Description
Monism	The brain and the mind are not distinct entities—the brain is the one true ontological[a] entity and the mind is a conceptual entity that allows us talk about functions of the brain that we cannot (yet) describe at the neuronal level
Physicalism	Each mind function is synonymous with some brain function
Reductionism	Each mind function can be reduced to some brain function
Dualism	The brain and mind are distinct entities
Interactionism	The brain influences the mind and the mind influences the brain
Parallelism	The mind and brain do not directly influence each other, although they operate in parallel

[a]Ontological: something that really exists in the world, not just a concept or idea

For example, a dualist might argue that while much is known about the neuroanatomic and biochemical correlates of emotion, including some of the very specific brain circuits involved, it is currently not possible to reliably define specific emotional states (emotion 'quality') in terms of specific neurophysiologic states (see [210]). That is, a neuroscientist cannot accurately "measure" the quality of emotion a person is experiencing based on patterns of activity in specific brain circuits. A monist would counter that our inability to define (i.e., reduce) highly specific phenomenological emotional qualities (e.g., joyful surprise versus fearful surprise) in terms of specific neurophysiologic states is due only to the limitations of current technologies for detecting these states. She would argue that once we have sufficiently refined technologies, we will be able to accurately describe all aspects of a person's emotional state (quality and intensity) based solely on patterns of neuroactivity. The dualist, in turn, would counter that there is no such future technology—that there is something fundamentally (ontologically) different between the way the mind manifests emotional qualities and the way the brain manifests them.

6.3.4 Epistemological Differences within the Behavioral and Social Sciences: A Multiplicity of Theories of 'Mind' and Behavior

If the theoretic and epistemic differences between the behavioral and biological sciences don't make your head spin, the multiplicity of theories within the behavioral and social sciences certainly will! Whereas disagreements between scientists and clinicians working in the biomedical domain tend to be primarily about nuanced mechanisms, and directions of causal relationships, scientists and clinicians working within the behavioral and social sciences often disagree about the fundamental entities and mechanisms themselves. Imagine working in research informatics in cardiology in a time before the existence of modern tools and technologies for visualizing the structures and function of the heart in a living human. Imagine two scientific camps within the field of cardiology—each one having a fundamentally different model of the structure and function of the heart. Imagine the number of competing entities, processes, and theories that scientists could justify based only on phenomena that could be directly observed. This is the current state of the behavioral sciences. The primary entity of interest—the mind—cannot be directly observed. Consequently, the functional properties of this key entity are defined in radically different ways within the behavioral sciences.

For informaticians working in MHI, the significance of these philosophical (theoretic) distinctions cannot be overstated. MHI embraces the spirit of the vision put forth by NIMH in the RDoC framework which strives to improve the process of acquiring knowledge across the diverse branches of science in which knowledge is being generated. To do this, informaticians working in MHI must be fluent in the many theoretical languages of the biological, behavioral, and social sciences. At minimum, this means understanding the nuances of the data-to-knowledge process employed by each field. This includes understanding how the field defines and models the real-world phenomena of interest as well as how the field identifies, captures, and represents these phenomena (signals) in the form of quantifiable data points. It includes understanding the paradigms and computational (statistical, analytic) methods the field uses to transform these data into meaningful information, and then into actionable knowledge.

6.3.5 Points of Intersection Between the Biological, Behavioral, and Social Sciences

Despite the many challenges inherent in bridging the gap between the biological and behavioral sciences, over time we are seeing increasingly more overlap between the sciences (Fig. 6.7). This impetus is coming from within each of the sciences

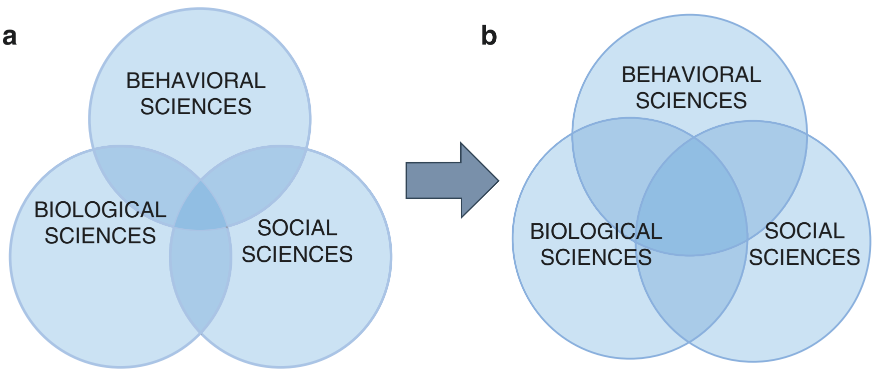

Fig. 6.7 (**a**) Relationship between phenomena of interest in the biological, behavioral, and social sciences. (**b**) Increasing overlap between phenomena of interest in the biological, behavioral, and social sciences as more is understood about the interrelationships among them

themselves and there has been great progress in understanding the complex, reciprocal ways in which biological, behavioral, and social phenomena mutually influence each other. Increasingly, behavioral and social scientists are asking sophisticated questions about the mechanisms by which biological, mental, behavioral, and social phenomena influence each other [211–214]. Similarly, biological scientists are developing novel methods for investigating not only the ways that biological functions drive mental and behavioral functions, but conversely, the ways that mental, behavioral, interpersonal and social functions drive biological functions [157, 159, 160, 163]. This knowledge is being generated by interdisciplinary scientists working explicitly at the intersections of the biological, behavioral, and social sciences (Fig. 6.6).

While there is strong consensus that biological underpinnings of many, if not most, mental and behavioral phenomena will undoubtedly be discovered as technologies for assessing both neurobiological and mental phenomena become more sophisticated [100, 110, 112], the real challenge lies in identifying the causal direction and mediating variables in these relationships. In some cases, as we understand more about the brain and the physiological underpinnings of the associated mental and behavioral phenomena, the differences between mental and biomedical disorders may begin to fade [100, 110, 112]. Those psychiatric disorders discovered to have a clear, primary biologic etiology may be re-categorized as biomedical disorders, e.g., as neurological or endocrine disorders [98]. In other cases, discovery of the biological underpinnings of mental health conditions may provide insight into ways that different social and interpersonal experiences shape our brains in ways that lead to long term dysfunction or distress.

6.4 How Mental Health Informatics Extends Informatics

Above we focus on the differences between MHI and other informatics subdisciplines, and on ways in which mainstream biomedical and health informatics has neglected the behavioral and social sciences. However, several mainstream informatics technologies are being heavily utilized in the field of mental health. For example, the use of mobile health technology (mHealth) has been an area of increasing interest in medicine in recent years due to both the ubiquity of smartphones and the development of new technologies such as activity trackers and smartwatches [215]. Given the importance of activity-related behavior in risk, diagnosis, and treatment for mental health conditions, this technology has been game-changing for data-driven study and treatment in mental health [196, 216, 217] (see Chap. 17).

Natural language processing (Chap. 13) is a major subfield of informatics with NLP paradigms routinely applied across scientific literature, clinical text, and social media alike [218–222]. It is particularly useful in the context of mental health, where symptoms and environmental factors) are often recorded only in free text and rarely as structured data or as results of quantitative assessments. Social media in particular is a rich source of the kinds of information of interest to behavioral and social scientists (e.g., emotion, thoughts, behavior, social interaction, and environments). Moreover, social media can be an outlet for people struggling with mental health concerns, whether to vent privately to friends on Facebook, or to share their distress with the world through Twitter [221, 223, 224]. Information shared in these places may rarely make it to a healthcare provider's radar but can be invaluable for tracking a person's mental health over time.

Ethical, legal, and social issues (Chap. 18), particularly around data privacy and security, are important in informatics at large, but particularly so for mental health data due to the stigma that is unfortunately still attached to these conditions. Substance use disorder (SUD) information is even more sensitive, protected under its own legislation, 42 CFR (Code of Federal Regulations) Part 2 prohibiting unauthorized disclosures of health records except in limited circumstances [225].

Arguably the most important way in which MHI extends traditional informatics is by focusing our attention on the many implicit assumptions we make, and the beliefs we hold, about the nature of the relationship between the underlying entities and processes about which we seek knowledge, and the concrete data that serves as their proxies in our knowledge acquisition paradigms. Because informaticians working in mental health deal with fundamentally different kinds of things than those working in biomedicine, and because the paradigms used to isolate and measure these phenomena are fundamentally different from the paradigms used in biomedicine, mental health informaticians cannot take for granted that the data generated from traditional sources accurately and complete represents the underlying phenomena of interest. Consequently, mental health informaticians will likely elucidate critical aspects of the early phases of the DIKA process: the process by which the observable signals produced by real world phenomena become concrete data—linguistic representations with associated quantitative and qualitative metrics.

6.5 Summary

The relatively young field of Mental Health Informatics overlaps significantly with the broader field of Biomedical and Health Informatics, but also extends some existing aspects of the field, and introduces new complexity and challenges derived from its unique position at the confluence of several different branches of science: the biological, social, and behavioral sciences. Complexity within the social and behavioral sciences in terms of the multiplicity, and sometimes inconsistency among, models of mental and behavioral function further contribute to the challenges. As described in detail in the discussion of epistemological differences between the social and behavioral sicences on the one hand and the biological sciences on the other, as well as the discussion about the historical roots of informatics in the biological sciences, mental health informaticians will be required to adopt new paradigms for knowledge discovery. One important areas of work will be reconciling different approaches to concept and knowledge representation (Chap. 7). Another will reconciling different approaches to knowledge acquisition itself (see Chap. 12). Finally, significant advances in technologies for signal detection, the acquisition of data, methods for transforming data into knowledge, and opportunities to apply that new knowledge in both standard and novel avenues for mental healthcare pose tremendous opportunities for students, researchers, and practitioners in this exciting field.

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