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Fostering Information Disclosure in Telemental Healthcare Settings: How Telehealth Can Mitigate the Deleterious Effects of Stigma

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Abstract

Insufficient patient disclosure and persistent stigma undermine effective mental health care, a challenge magnified during the COVID-19 pandemic. Telehealth offers a promising avenue to reduce access barriers and improve equity, yet its effectiveness depends on patients' willingness to disclose sensitive information online. This study develops a middle-range, contextually adapted version of the disclosure processes model (DPM) to explain and predict how stigma and technological features shape online self-disclosure in mental health settings. We conducted a randomized web-based experiment with 309 participants who viewed a video vignette depicting a consultation between a patient and a psychiatrist. The vignette manipulated diagnosis (ADHD vs. schizophrenia) and consultation mode (in-person vs. virtual). Results show that willingness to disclose increases with greater trust in technology, higher perceived social presence, and richer communication media. Initial disclosure goals align with differing levels of technological trust and self-disclosure. However, perceived stigma weakens these positive relationships, reducing patients' readiness to share sensitive information. The research advances theory by extending the DPM into a context-specific, middle-range information systems framework that integrates stigma and media characteristics in online mental health care. Practically, the findings identify key communication features—such as social presence, richness, and trust in telehealth platforms—that can be calibrated to foster disclosure of stigmatized information. These insights inform the design and implementation of telehealth services that promote open communication and improve treatment engagement in mental health and other stigma-laden domains.

Keywords: Information disclosure, disclosure processes model (DPM), mental health, telehealth platform, telehealth information disclosure model (TIDM), communication medium characteristics, stigma, social

presence and information richness (SPIR), theory contextualization, middle-range theorizing, theory building

Introduction

The early 2000s witnessed a marked escalation in mental health disorders, leading to the characterization of this trend as the "silent epidemic" of the 21st century, with the WHO recently estimating that over one billion people live with mental health conditions.[1] The onset of the COVID-19 pandemic further exacerbated this crisis because it led to deterioration of mental health, widespread income loss, social isolation, and unemployment fears [138]. Crucially, mental disorders account for the loss of approximately twelve billion global workdays annually [139]. The global, escalating prevalence of mental illnesses poses an alarming threat, with projections estimating a global financial impact of $16 trillion by 2030.[2] As grim as this financial trajectory seems, it is far from the only undesirable outcome of the mental health crisis. This crisis exerts a profound psychological and emotional toll on individuals, families, and communities, ultimately affecting society. These consequences extend far beyond financial costs, encompassing cognitive decline, intellectual dysfunctions, and, in some cases, fatalities [28, 104, 128]. This multifaceted crisis underscores the urgent need for comprehensive strategies to mitigate its wide-ranging societal effects.

Among the salient impediments to resolving the escalating global mental healthcare crisis are stigmatization and accessibility [81, 111, 115]. With its distinctive capabilities, telehealth has emerged as a viable solution to address these critical issues, presenting a practical approach to managing the burgeoning mental health crisis [17, 99]. During the COVID-19 pandemic, telehealth use surged, especially in mental health. The proportion of telemental health providers increased from 17% before the pandemic to 40% during the pandemic, with the percentage of providers' caseloads served remotely jumping from a mere 9.1% to 57.7% in the same time frames [146]. Although telemedicine visits declined after the COVID-19 pandemic, mental health video visits continued to increase [50]. These statistics highlight the substantial shift towards telehealth in mental healthcare and emphasize the timeliness and relevance of our study in this context.

Telemedicine has long been recognized for expanding access to healthcare [83, 109], and recent studies show that mental health service users perceive less *stigma*[3] when using telehealth compared to in-person

care [14]. This suggests that virtual environments offer a more comfortable space for self-disclosure, which is essential for accurate diagnosis and effective treatment in mental health settings. These structural advantages align with broader efforts to meet increasing mental health demands via digital platforms [59].

What needs to be emphasized is that, regardless of modality, the patient's willingness to disclose personal information is a key determinant of effective mental health care. Without the willingness to share personal information, individuals may delay or avoid seeking necessary care [59]. This disclosure is often inhibited by perceived stigma, a condition that has been shown to significantly reduce self-disclosure across a range of stigmatized conditions, including mental illness, sexually transmitted infections, abortion, and addiction [25, 34, 58].

Although there is substantial research on self-disclosure in online environments, studies explicitly focusing on self-disclosure within stigmatized environments are limited [5, 116]. This indicates a gap in the literature regarding online information self-disclosure in various stigmatized settings. The role of the telehealth platform in shaping patient reassurance and self-disclosure remains underexplored. Although some research has identified factors influencing disclosure in digital health [59], there is limited understanding of how specific features affect user behavior. Evidence from videoconferencing-based telemental health suggests that certain technological aspects (e.g., self-view features or seeing yourself on camera) may cause discomfort, highlighting the need for targeted research on how platform characteristics affect self-disclosure, particularly in stigmatized contexts [23]. Although some patients report enhanced comfort with videoconferencing, others experience discomfort or self-consciousness during digital sessions [10]. These mixed responses point to the platform's potentially significant, but underexplored, role in shaping disclosure experiences. Accordingly, this study seeks to address critical gaps at the intersection of self-disclosure, stigma, and telehealth.

Pragmatically, under-disclosure in the telehealth context, if unaddressed and particularly in intake, will persist, thereby undermining diagnosis, care planning, safety screening, and equity for stigmatized groups. Clarifying this mechanism enables actionable design and clinical guidance when information disclosure matters the most. Theoretically, not addressing the aforementioned gap raises several key questions: How

can platform-context cues (e.g., SPIR) shape disclosure behavior in online settings, and how can trust in the IT artifact affect disclosure in the telehealth context? Finally, how will stigma influence all these variables? Also critical is the role of antecedent disclosure goals, which have been shown to influence information disclosure in traditional settings (e.g., in-person communication) [19, 20].

This research examines whether such factors amplify or dampen online disclosure. All in all, it builds on substantial prior research on self-disclosure in online environments and, given the dearth of previous work in the extant literature, expands on past work by focusing explicitly on technology-enabled information disclosure in stigmatized contexts [5, 116].

The *disclosure processes model* (DPM) is a relatively new molar-level theory that consolidates decades of findings and provides a valuable theoretical foundation for understanding the information disclosure process in sundry stigmatized areas. Our study adapts the DPM to the specific contexts of mental health issues and telemedical technology, thereby expanding this theoretical model to encompass technology-enabled environments [75]. The DPM focuses on information disclosure as the outcome variable, conceptualizes stigma as a salient contextual factor, and positions disclosure goals as major drivers of this process. Hence, it can be regarded as an excellent theoretical basis for our study [19, 20]. To our knowledge, no other theories conceptualize the disclosure process in stigmatized contexts so pointedly while integrating key variables of interest depicted above. This argues for the DPM as an organic and fitting choice.

Within this framework and taking one step further, factors such as trust in the IT artifact and the communication medium's social presence and information richness (SPIR) are hypothesized to enhance the explanatory power of the DPM concerning online information disclosure. Contextualizing the DPM in this manner results in a novel middle-range theory. Middle-range theorizing represents a notable form of meaningful theoretical contribution because it balances abstraction and empirical grounding, allowing for broad generalizations and insightful conclusions while remaining closely tied to observable data for validation [61, 65, 66]. This method fosters the development of original and influential theories, offering a fresh alternative to the repetitive rearrangement of variables derived from grand theories that frequently characterize information systems research.

The high-level objectives of this study are, therefore, twofold: first, to contextualize a highly relevant grand theory from psychology and turn it into a practical middle-range health information systems (IS) theory by introducing technology-specific constructs (e.g., social presence and information richness of the communication medium and trust in the IT platform) and context-specific constructs (e.g., stigma) into the model, thereby granting it explanatory power in online settings. The second goal is to empirically test this proposed model to investigate how these new constructs (e.g., stigma and SPIR) influence clients' information self-disclosure in the telemental health setting. This combination of theoretical and empirical exploration offers significant insights, both theoretical and practical. The research focuses on the VSee platform, a renowned, HIPAA-compliant telehealth videoconferencing system. VSee's use in the mental health sector underscores its significance as the primary IT artifact under investigation in this study. The methodology involves an online experimental design that empirically tests the applied theory with a randomized sample of 309 participants. The central research questions are:

RQ1. What theories explain how disclosure goals and trust in technology affect online self-disclosure in a telemental healthcare context where stigma is likely?

RQ2. Which characteristics of the communication medium promote the sharing of stigmatized information in a telehealth mental-healthcare context, and how do they work?

Telemedicine for mental healthcare (i.e., telemental healthcare) is positioned as an essential solution to the mental health crisis. This assertion is grounded in the literature discussing virtual medical appointments and telemedicine as strategies to mitigate essential mental healthcare challenges. Subsequently, the DPM is employed to demonstrate how trust in technology can enhance information sharing and facilitate the adoption of virtual appointments. The research further examines the negative impact of stigmatization on a broad spectrum of mental health disorders and illnesses, citing its role as a fundamental deterrent to seeking treatment [88, 113]. The investigation assesses how specific characteristics of the communication medium, in the context of stigma, can increase the likelihood of information disclosure and help-seeking behaviors [31, 67, 91]. The overarching aim is to improve access to mental healthcare. The findings of this study are poised to provide valuable guidance for scholars and practitioners, informing them about the specific characteristics of the communication medium that facilitate the disclosure of stigmatized information, thereby advancing the

field of mental healthcare.

Background: Mental Health and Telemedicine

Many individuals who could gain from mental health services choose not to seek help or do not fully engage after starting treatment. A key factor behind this gap is ***stigma,*** because people often avoid care to escape being labeled with a mental illness and the negative consequences associated with it [33]. Increased accessibility to mental health services is associated with reduced patient risk and improved mental health outcomes. However, mental health resources are inadequate in almost every country worldwide [117, 127]. Taken together, stigmatization and limited accessibility of services are critical barriers to a comprehensive solution for the global mental healthcare crisis [81, 111]. Compounding this challenge is a projected shortfall in qualified mental health personnel. Globally, mental health remains one of the most underfunded sectors in medical care and research, with this severe underinvestment being even more pronounced recently [98, 117]. As an illustration, in the US, over 122 million Americans live in mental health professional shortage areas in 2025, and it is projected that by 2037, there will be a shortage of 88,000 mental health counselors and 114,000 addiction counselors.[4]

The COVID-19 pandemic galvanized an unprecedented surge in telemedicine adoption among healthcare providers and patients. Telehealth services in hospitals have dramatically increased, rising in some cases from < 1% before the pandemic to 70% by 2020 [118]. A national study using insurance claims data highlighted a 766% increase in telemedicine usage in just the first three months of the pandemic, and this trend has persisted chiefly post-pandemic [106, 120]. This shift towards telehealth represents a pivotal development in addressing accessibility issues in mental healthcare.

The advent of the Internet, virtual appointments, video conferences, and telemedicine is increasingly recognized as a globally accessible and cost-effective response to healthcare challenges [142]. With its unique features, telehealth addresses accessibility and cost issues in healthcare. Telemedicine, long regarded as a solution to numerous healthcare challenges, offers expanded access to care [10, 83, 109]. Telemental healthcare, despite being available for years, gained significant traction as a viable alternative to in-person therapy only during the COVID-19 pandemic, which catalyzed its adoption as an

underexploited technology. Robust evidence confirms that telemental health—delivering behavioral and mental health services via technologies such as videoconferencing and mobile applications—is highly effective in managing a broad spectrum of mental health disorders [e.g., 1, 2].

The current mental health crisis presents an opportune moment for increasing the deployment and adoption of telemental health. Its applications, notably in counseling, triaging, and screening, are particularly relevant. This trend is further underscored by the marked increase in mental health issues in the world since the early 1980s—a development that emerged well before the advent of the Internet. The rate of people utilizing or needing mental health treatment escalated from about 1 in 10 in the 1980s to more than 1 in 5 by 2023 [89]. This surge is attributed to two primary factors: a societal shift towards greater acceptance of reporting mental health issues, leading to increased treatment-seeking behaviors, and a rise in the prevalence of various mental illnesses [89]. With its growing global footprint, Telehealth is poised to enhance access to care and enable more efficient patient-physician interactions at a lower cost than traditional mental care approaches. This shift is expected to improve health outcomes.

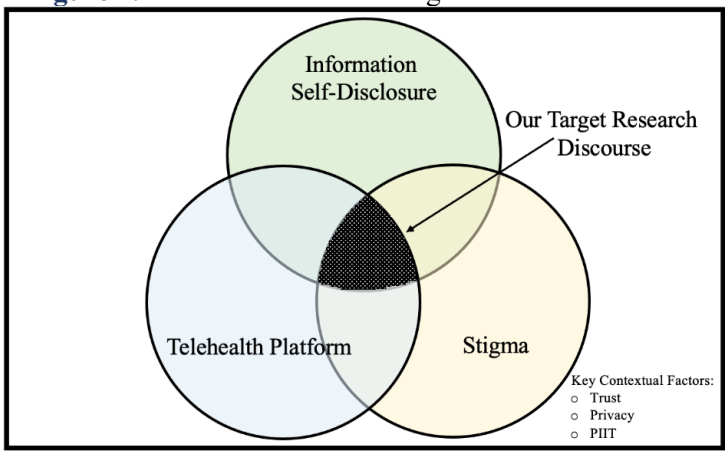
Another crucial element in seeking mental healthcare is clients' self-disclosure. Effective treatment remains attainable with such disclosure, whether through traditional care or technologically facilitated methods, such as telemedicine. The willingness to disclose information is often diminished by the perceived stigma associated with mental illnesses, with studies demonstrating a significant inverse relationship between stigma perception and patient disclosure [25, 34]. This inverse effect of perceived stigma on information self-disclosure is observed in generic contexts, mental health therapeutic settings (both online and in-person), and other stigmatized contexts like sexually transmitted diseases, abortion, anorexia, and alcoholism [25, 34, 58].

Recent studies indicate that mental health service patients experience less perceived stigma with telehealth than with traditional face-to-face interventions. This suggests that virtual environments may foster a more comfortable space for self-disclosure—particularly for individuals who might otherwise be reluctant to share sensitive personal information in conventional settings [14]. Information self-disclosure is a critical initial step toward help-seeking behavior in the mental health context. Accurate diagnosis and

effective treatment are impossible without a patient's willingness to disclose personal information [59].

Although there is substantial research on self-disclosure in online environments, the few studies explicitly focusing on online self-disclosure in stigmatized contexts are limited [5, 116]. In addition, the influence of technology design on self-disclosure and stigma in telehealth platforms warrants further exploration. Although existing research has begun to identify factors affecting information self-disclosure in digital health settings, few studies specifically address how platform features impact user disclosure behaviors [59]. Additionally, studies on videoconferencing-based telemental health suggest that the medium itself may affect rapport and self-disclosure, with patients potentially experiencing self-consciousness and discomfort during sessions; yet others prefer the digital medium [10]. Hence, certain technological aspects could significantly influence disclosure behaviors, but detailed examinations of which design features contribute to these feelings are few and far between [23]. Therefore, targeted research is badly needed into how specific telehealth platform characteristics affect users' self-disclosure of personal information, especially in stigmatized settings. The current study aims to fill these crucial gaps at the intersection of information self-disclosure, stigma, and telehealth platform features. **Figure 1** visualizes this intersection and highlights our target research discourse (along with key factors controlled for in our study).

Figure 1. Visualization of the Target Research Discourse



Note: PIIT represents personal innovativeness with information technology.

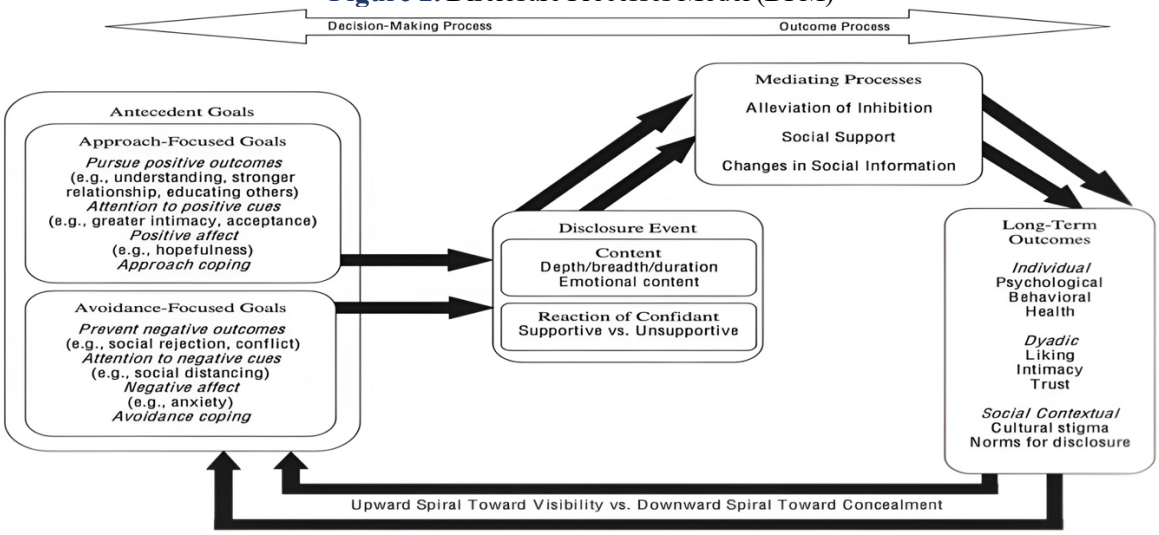
Theory and Hypotheses: The Disclosure Processes Model

Effective treatment of mental illness often hinges on individuals recognizing their problems and disclosing them to a mental health professional. An essential factor in delivering effective mental health care, whether

in person or digitally, is the individual's readiness to share personal information. When patients are unwilling to disclose, they may postpone or entirely forgo accessing the care they need [59]. A major barrier to such disclosure is perceived stigma, which has been consistently linked to reduced willingness to share in contexts marked by stigma, such as mental illness, sexually transmitted diseases, abortion, and substance abuse disorders [25, 34, 58].

To understand this process, the DPM serves as a theoretical foundation, offering insights into information disclosure for various stigmatized conditions, including mental health disorders, abortion, epilepsy, and HIV/AIDS. Initially set forth to explain the decision-making and post-disclosure outcomes in cases of concealable stigmatized conditions, the DPM focuses primarily on the decision-making and outcome processes related to information disclosure. It describes the circumstances under which information disclosure can be beneficial [19]. Adapted from Chaudoir and Fisher [19], **Figure 2** depicts the original DPM, which has two principal components: decision-making and outcome processes.

Figure 2. Disclosure Processes Model (DPM)



Note: This is the original figure in Chaudoir and Fisher [19]. Permission to reproduce has been secured from the APA.

In stigmatized contexts, where self-disclosure may cause shame or embarrassment, *information disclosure* is formally defined as the verbal conveyance of self-relevant data, encompassing individuals' thoughts, feelings, and experiences [40]. In such contexts, the influence of antecedent disclosure goals is also essential, as these pre-existing intentions have been shown to shape individuals' decisions to share

information in various settings [19, 20]. Prior literature highlights that antecedent goals can be of two different natures: promotion goals, approach-focused, centered on gains and striving for positive outcomes, or prevention goals, avoidance-focused, centered on loss and preventing adverse outcomes [15, 19, 20]. *Disclosure goals* are the initial intentions influencing the likelihood of disclosing information in a given situation. The DPM suggests that disclosure initiation is primarily governed by these disclosure goals, thereby setting in motion a decision-making process [108].

Overall, the current study builds on a robust body of prior research on self-disclosure in online settings and extends it by explicitly examining technology-facilitated information disclosure within stigmatized contexts—a critical area that remains notably underexplored in the existing literature [5, 116]. DPM is the theoretical foundation for our study because it is a relatively new molar-level theory that consolidates decades of research on self-disclosure and offers an insightful conceptualization of the information disclosure process, specifically in stigmatized environments. Information disclosure is this paper's primary variable of interest, and mental health is the context of interest. Before patients can be effectively treated for mental illness, they most often need to recognize and admit that they are experiencing problems and disclose these problems to a mental health professional.

The Disclosure Processing Model (DPM) focuses explicitly on information disclosure as the primary outcome and uniquely frames stigma as a critical contextual factor while highlighting disclosure goals as key motivational drivers in the process [19, 20]. To our knowledge, no other theoretical framework offers a comparably clear and integrated account of the disclosure process within stigmatized contexts, making the DPM the most coherent and appropriate theoretical anchor for addressing the specific objectives of this study. Accordingly, the DPM, which explains information disclosure across various stigmatized conditions, serves as the theoretical foundation. Our scoping is on the left-hand side of the original model, conceptualizing the information disclosure decision-making process. The right-hand side of the model, revolving around the outcome process and post-disclosure events, is out of scope. Before settling on the DPM, another theory was considered and eventually discarded due to inferior fit. For more details, see Appendix D.

Based on other relevant nomologies and contributing research streams, further justifications for the inclusion of our primary variable of interest (i.e., information disclosure) were identified, and several critical situational factors were identified and controlled for (e.g., trust in doctors, privacy concerns, and personal innovativeness with information technology). Social exchange theory highlights that the cost of disclosure under risk (e.g., when sensitive information is involved) can influence the decision to disclose. In contrast, health communication theory underlines disclosure as a clinical process outcome. Together, these two theories shed light on the importance of perceptions of alternative options and different communication channels [12, 36] and pave the way for incorporating face-to-face versus online communication as the baseline for our comparison, instantiated in the experimental design.

The *technology acceptance model* (TAM) research stream also provided further insights, helping to theorize and contextualize the DPM. Most notably, social presence and information richness (SPIR) were essential characteristics of the communication medium derived from the TAM literature. As a high-level communication medium with characteristics applicable to more nuanced telehealth options in future studies, SPIR helped us further enrich the technology-related aspects of our proposed model.

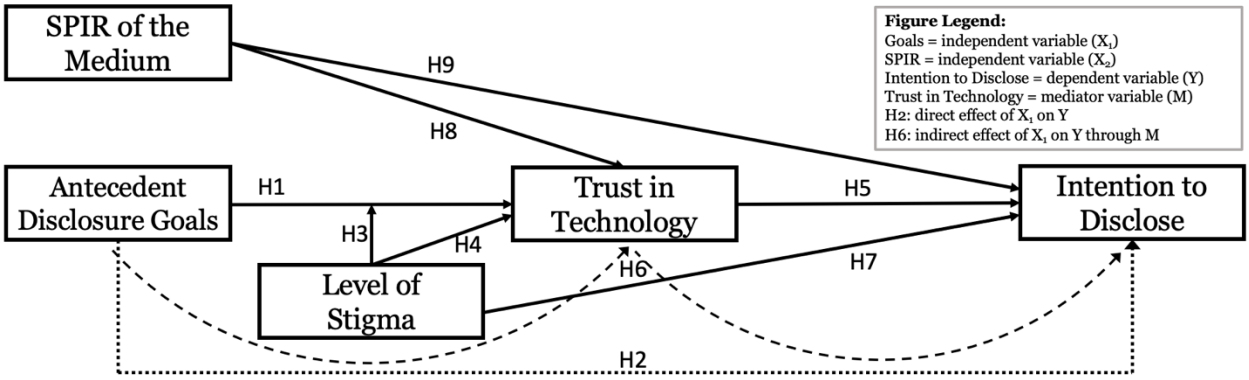
It should be noted that TAM researchers later recognized that trust in the platform can be critical in a variety of situations [62] as when users must rely on systems that handle sensitive information or when risks are present (e.g., in healthcare and e-commerce) [131]. In areas like telehealth, where privacy and security concerns are high, trust significantly influences users' willingness to adopt and use technology, thereby affecting the clinician-patient interaction [43]. Thus, trust in the technological platform should be a major enabler of adopting telemental health solutions; hence, we included it in the research model and controlled it vis-à-vis different aspects of trust.

Contextualizing the DPM for Trust in Online Stigmatized Mental Health Disclosure

Given that the outcome process falls outside the intended scope of this study, the focus here is on the decision-making process, as delineated on the left side of the DPM. **Figure 3** presents an adapted and testable telehealth information disclosure model (TIDM) that contextualizes the DPM decision-making process in online stigmatized mental health disclosure scenarios. In stigmatized conditions, in which self-

disclosure may cause shame or embarrassment, *information disclosure* is formally defined as the verbal conveyance of self-relevant data, encompassing individuals' thoughts, feelings, and experiences [40]. In such contexts, the influence of antecedent disclosure goals is also significant, as these pre-existing intentions have been shown to shape individuals' decisions to share information in various settings

Figure 3. Telehealth Information Disclosure Model (TIDM)



[19, 20]. Prior research highlights that antecedent goals can be of two different natures: promotion goals, approach-focused, centered on gains and striving for positive outcomes, or prevention goals, avoidance-focused, centered on loss and preventing adverse outcomes [15, 19, 20]. The following *Disclosure goals* are the initial intentions influencing the likelihood of disclosing information in a given situation. The DPM suggests that disclosure initiation is primarily governed by these disclosure goals, thereby setting in motion a decision-making process [108].

The patient's willingness to disclose personal information is also a key determinant of effective mental health care, regardless of modality. Without the willingness to share personal information, individuals may delay or avoid seeking necessary care [59]. Therefore, in our contextualized model, *goals* became the obvious independent variable (IV) and *information disclosure* the dependent variable (DV), both of which are foundations in the original DPM.

The molar-level psychological DPM theory has thus been contextualized as a practical, middle-range IS theory by introducing into the model, technology-specific constructs — social presence and information richness (SPIR) of the communication medium [22, 96] along with trust in the IT platform [101, 102, 132] and context-specific constructs (e.g., stigma) [16, 134], thereby granting it greater explanatory power for

online settings. This problem-focused middle-range theorizing is a considerable theoretical contribution [61, 65, 66]. Middle-range theories are sufficiently abstract to enable generalizations and meaningful conclusions while remaining grounded in observed data within a limited conceptual range or scope, thereby facilitating empirical validation [71, 103]. Because of its focus on the pragmatic connections among problems, theory, data, and context, this approach to theorizing can generate innovative and impactful theories, moving beyond the routine, repetitive reshuffling of variables drawn from overarching theories that often dominate information systems research [61, 65, 66]. To propose and test the TIDM, the applied DPM incorporated factors specific to mental health stigma and technological elements. These elements include the level of stigma associated with mental health conditions, the SPIR of the communication medium, and a patient's trust in the IT artifact, all of which are pivotal in determining online disclosure by patients with stigmatized conditions. In this recontextualization, the original antecedent goals of the DPM serve as the IV. Moreover, the intention to disclose stigmatized information is a proxy for the DV's actual disclosure event.

The DPM has not been previously contextualized to capture the unique aspects and complexities of technology-enabled online disclosure in stigmatized situations. The TIDM distinguishes itself from the traditional DPM through three distinct constructs that further explain patient information disclosure: (1) trust in the technological platform, serving as a mediator; (2) the level of stigma attached to various mental health disorders, functioning both as a moderator and an IV; and (3) SPIR, derived from the TAM literature, acting as a crucial predictor in the disclosure process. In our experimental design, both stigma level and SPIR were directly manipulated, laying the groundwork for causal inference.

Disclosure Goals, Trust in Technology, and Stigmatization

Trust is crucial in disclosure settings [114]. This study examines trust from multiple perspectives: dispositional trust attitudes, trust in physicians, and trust in technology. Notably, given the pivotal role of telehealth platforms as enablers of online disclosure and because of the specific goals of our study, trust in technology is a key factor acting as the mediator in our conceptualized model, whereas the first two constructs (see above) are controlled for due to their less central (but still important contextual) role (see

Figure 3). To assess these dimensions, patients' inherent disposition to trust, their trust in their doctor, and their trust in the technology were all measured. Dispositional trust is the general tendency to trust others [55]. Trust in physicians is defined as interpersonal clinician–patient trust (willingness to be vulnerable to a specific clinician)[8].

Based on prior literature [101, 102] trust in the technology platform can be defined as institution-based trust that focuses on the belief that legal measures and technological safeguards on the Internet, such as data encryption, protect individuals from privacy and identity breaches and contribute to positive results (e.g., improved clinical outcomes in healthcare). This last type of trust highlights the platform's intermediary role in providing a supportive technical and procedural environment. Trust in technology is, from another perspective, the belief that technological (and other) platform structures and protections, such as data encryption, safeguard and protect one from adverse outcomes and create a sense of safety and comfort in using the IT platform for a virtual therapy session [101, 102].

Preliminary data collection on participants' inherent trust tendencies and their trust in their physician helped control for variations in how the experimental IT artifact influenced trust in the technology (i.e., the online platform), the primary variable of interest in this study. **Figure 3** shows that trust in the telehealth platform is central to the TIDM. Because the telehealth platform is operationalized as a specific online videoconferencing provider (i.e., VSee), we adopted and modified a previously validated measure of institution-based trust [102], emphasizing web-related structural assurance of the platform, as this can safeguard patients against the loss of privacy and the sharing of highly personal information during a therapy session. This was instrumental, as this specific dimension of trust in technology is expected to influence one's willingness to disclose personal information directly (we did not measure the situational normality aspect of institution-based trust because it also applies to other non-web-based providers, such as brick-and-mortar providers or offices). Our specific instantiation of trust is the most relevant to our study and distinct from other, more generic trust-based IS theories, such as trust in vendors and general trusting beliefs and intentions [56, 101, 102].

Like the DPM, our research identifies two types of disclosure goals: approach-focused and avoidance-

focused. Patients with an approach-focused mindset aim for positive outcomes (e.g., understanding and more robust relationships). They are attentive to positive cues (e.g., acceptance, higher levels of intimacy) and to affective states such as hopefulness. Conversely, patients with an avoidance-focused attitude concentrate on averting adverse outcomes (e.g., conflict and social rejection). They are alert to negative cues and affective states, such as social distancing and anxiety [19].

According to the DPM, people with approach-focused goals tend to focus on positive cues, such as enhanced intimacy and acceptance. This orientation aligns with prior literature suggesting that patients with a positive attitude toward technology are more likely to adopt approach-focused goals [19, 100]. Such individuals are inclined to notice positive stimuli [41], exhibit positive attitudes towards social connections, including the therapist-patient relationship, and generally experience more frequent positive affect [53]. Consequently, they are predisposed to perceive the telehealth medium favorably, hence exhibiting greater trust in the technology.

Conversely, people with avoidance-focused goals are attuned to negative cues, like social distancing. This perspective is consistent with existing research [19, 100], particularly when they harbor negative attitudes toward technology. Such persons are more likely to be sensitive to negative stimuli [41], tend to interpret ambiguous or neutral stimuli negatively (such as user interface design features of a telehealth platform) [123], and generally experience a higher frequency of negative affect [53]. As a result, they are less inclined to view the technological platform positively, demonstrating lower acceptance and trust in the technology.

The DPM assumes that a person may simultaneously possess both approach- and avoidance-focused goals. This understanding has guided the research design, in which these antecedent goals are aggregated into a single continuous variable, as detailed in the methods section. Theoretical constructs sometimes involve conflicting logic, with no distinct positive or negative relationships between variables. In such cases, particularly when evidence supports both directions, as with approach- and avoidance-focused antecedent disclosure goals in the DPM, it is rational to formulate a theory based on specific contextual factors [78], recognizing that the theory or its components might not be universally applicable in all settings

due to unique enabling or disabling conditions [60].

In online environments such as telehealth, patient unfamiliarity introduces additional uncertainties. Heightened uncertainty and vulnerability have also been identified as salient factors in mental healthcare [16]. These uncertainties can amplify negative cues like fear, which are particularly influential for individuals with avoidance-focused goals [19] and foster emotion-focused coping instead of adaptive coping [141]. Building on Witte [141], privacy and security research in IS similarly shows that too high levels of threat, fear, risk, and uncertainty can lead to counterproductive behaviors such as defensive avoidance and psychological reactance [21, 95]. The stigma associated with mental health illnesses also has numerous negative consequences, such as lower levels of trust and higher levels of uncertainty [16, 134]. Thus, in a neutral scenario where neither type of antecedent disclosure goal is active or manipulated — as in this study — it is logical to hypothesize that the average person's disclosure goals in a tele-mental health setting will be predominantly avoidance-oriented due to potential stigma.

Equally important is the role of trust. Prior studies show that the stigmatized nature of mental health illnesses leads to lower levels of trust in mental health service users [134]. Trust is essential in situations of vulnerability and uncertainty, which are particularly significant in the context of experiencing and treating mental illness [16]. Higher levels of uncertainty also lead to lower levels of interpersonal trust [42]. In addition, the processes that drive trust in technology are like those that govern trust in people [100, 132]. Against this backdrop, the primary concern is that patients with avoidance-dominated goals may avoid using a telehealth platform that could benefit them. We thus propose:

H1. Avoidance-dominated goals will lead to decreased levels of trust in the telehealth platform.

The DPM explains that approach- and avoidance-motivated behaviors fundamentally drive disclosure, shaping each phase of the disclosure process [19]. Again, people can simultaneously possess both goal types [19]. People with approach-focused goals, characterized by hopefulness, a desire for acceptance, and a tendency to initiate contact to understand better, are more likely to disclose stigmatized information as part of help-seeking behavior [19, 20]. In contrast, those with avoidance-focused goals, who typically exhibit anxiety, social distance, and a reluctance to make initial contact due to fear of social rejection, are

less inclined to disclose such information [19, 20].

Acknowledging the complexity and potential overlap of these motivations and following the reasoning applied in H1, a patient's disclosure goals are more likely to be dominated by avoidance in a telehealth setting where stigma is expected. In addition, individuals who perceive a higher stigma surrounding mental health are less inclined to seek treatment by sharing stigmatized information with a doctor [134]. Telehealth systems pose significant privacy and security risks that may undermine clients' willingness to adopt and use these platforms [64]. These privacy concerns are especially heightened for mental health clients due to the personal and stigmatized nature of the information shared with providers [51]. Thus, we propose:

H2. Avoidance-dominated goals will decrease the intention to disclose stigmatized information.

Mental health issues often carry a stigma and are frequently associated with negative connotations [88]. Stigmatization encompasses discrimination, the exertion of power against certain societal groups, prejudice, separation, stereotype endorsement, and labeling [88]. Such stigma invariably impacts help-seeking behavior negatively in the context of mental health [26]. Stigma manifests in various forms, including public stigma, treatment stigma, and self-stigma, all of which are pivotal in the mental health realm [79], and thus are controlled in our study. Despite their importance as salient contextual factors, these variables are controlled for in our research (rather than included in the main conceptualized model) because they are not central to this paper's objectives.

Aside from the previously mentioned different dimensions of stigma, the perceived disease-specific stigma associated with certain mental health disorders is a major factor influencing people's treatment-seeking behavior [68]. People perceive mental health problems as stigmatized and typically harbor cynical views toward those affected, subsequently regarding them as societal burdens [26, 32].

Disease-specific stigma, which plays a key role in our proposed model (see **Figure 3**), is defined as the extent to which stigma and negative connotations are associated with ADHD and schizophrenia (the two disorders mentioned in our study). A clear correlation exists between the level of stigma associated with mental health issues and diminished trust in others [134]. Intriguingly, the mechanisms underlying trust in technology mirror those of trust in people [100, 132]. Extending this logic, it follows that patients

associating stigma with mental health conditions (specifically schizophrenia and ADHD, in the present case) are likely to view the technology facilitating interaction more negatively. That is, patients with high stigma may fear judgment or data misuse, making them hesitant to trust the platform despite having disclosure goals. Conversely, patients with low stigma might feel safer and more trusting when intending to disclose. In our research, stigma is thus conceptualized as a negative moderator:

H3. The level of stigma negatively moderates the relationship between disclosure goals and trust in the telehealth platform.

People associating greater stigma with mental health issues tend to exhibit lower trust in others [134]. Trust in technology is founded on principles like those that shape trust in people [100, 132]. Telehealth systems pose considerable privacy and security risks that can undermine patients' trust and willingness of patients and clinicians to adopt and use these platforms [64]. Such privacy-related concerns are even more pronounced for mental health clients, given the sensitive, private, and stigmatized nature of the information being shared with providers [51]. Logical inference leads to the following hypothesis:

H4. Increased stigma levels reduce trust in the telehealth platform.

People who perceive greater stigma around mental health issues and consequently exhibit lower trust in others are less likely to seek treatment by disclosing stigmatized information to a doctor [134]. By extension, heightened stigma may diminish their trust in technology, given the parallel mechanisms of trust in technology and people [100, 132]. This diminished trust in technology could, conversely, increase patients' propensity to disclose private information to their doctors. Additionally, lower trust in people has been linked to decreased help-seeking behavior [134]. Thus, we hypothesize:

H5. Increased trust in the telehealth platform increases the intention to disclose stigmatized information.

Based on the earlier arguments for H1, people with avoidance-dominated disclosure goals will have lower levels of trust in the telehealth platform, especially in stigmatized settings like mental health. In addition, as argued in H2, such antecedent disclosure goals will also result in decreased intention to disclose stigmatized information on the telehealth platform. As argued with respect to H5, increased trust in the telehealth platform increases the intention to disclose stigmatized information on it. Finally, the

technological platform in a telehealth context is fundamental for facilitating communication between the patient and the doctor, enabling information disclosure. Consolidating the reasoning used in H1, H2, and H5, we propose:

H6. Trust in the telehealth platform fully mediates the relationship between avoidance-dominated disclosure goals and the intention to disclose stigmatized information.

Again, stigma consistently exerts a negative impact on help-seeking behavior in mental health settings [26]. A critical initial step in seeking mental health treatment, exemplifying help-seeking behavior, is information disclosure, particularly self-disclosure. *Self-disclosure* is the intentional and voluntary sharing of personal information with others [40, 114]. Based on this understanding, we propose:

H7. Increased stigma levels decrease the intention to disclose stigmatized information.

Social presence is the degree to which a medium allows users to experience others as psychologically present [125]. It is recognized as a critical characteristic of the communication medium that positively affects trust in the communication medium [130]. Information richness of the medium depends on the interactive nature of the feedback channel type (e.g., body language, facial expression, and tone of voice), the source's personal quality, and the interface's ability to express linguistic innuendos [125]. Like social presence, information richness is particularly relevant in long-distance communication technologies and positively influences trust perceptions [22, 90]. Prior research indicates that social presence and information richness (i.e., SPIR) collectively enhance trust in various technologies [22, 96]. Therefore, we hypothesize:

H8. Increased SPIR levels increase trust in the telehealth platform.

The interaction medium during therapy sessions is crucial, especially given the often stigmatized nature of the information shared [30]. Different interaction modes, such as face-to-face and virtual, demand varying levels of SPIR [125]. SPIR influences user behavior [67, 125], and in the context of mental health services, where information sharing and self-disclosure are paramount [82], increased SPIR should encourage greater self-disclosure. Because SPIR positively impacts trust in technology, facilitating online interactions, we propose:

H9. Increased SPIR levels increase the intention to disclose stigmatized information.

Important Control Factors

Two critical factors that influence information disclosure are trust and privacy concerns. Trust is essential; with it, people are more willing to disclose personal information [107]. In our study, trust encompasses several aspects: a general disposition to trust, trust in specific individuals (doctors, in this case), and trust in technology [102, 144]. The disposition to distrust also plays a vital role in this research discourse [49]. Disposition to distrust [49] was considered a separate control, recognizing that different mechanisms underpin trust and distrust and activate distinct brain regions [45, 105]. Privacy is another fundamental element affecting information disclosure in general scenarios and online environments [44, 126]. Thus, our study controls for variables related to trust/distrust and privacy to comprehensively consider the main contextual factors influencing information disclosure.

Privacy concerns are essential determinants of information disclosure in self-disclosure technologies [91, 147], in healthcare in general [6], and in telehealth, precisely [13, 38]. The significance of privacy concerns in fostering information disclosure within telehealth contexts has been well-established [13, 38]. A key privacy-related factor in these studies is an individual's overall concern for privacy, which is particularly pertinent and influential in online personal health disclosure [3, 143]. This concern is paramount given the sensitive and often stigmatized nature of the disclosed information [7], thereby warranting its inclusion as a control variable. See section 4.5 for full details on the controls and measures.

Methodology

A randomized, web-based experiment on telehealth solutions was conducted to evaluate TIDM rigorously. The online milieu was an ideal choice, given that telemedicine, including services such as online counseling, primarily operates through web channels [46, 129]. This web experiment approach also presented several benefits, notably: (1) its practicality during COVID restrictions, which precluded in-person participant involvement in a physical laboratory setting; (2) the facilitation of a substantial participant pool, enhancing statistical power; and (3) the capacity to identify and control for potential motivational confounders [136].

Pilot Testing and Final Participant Sampling and Procedures

The study's protocols, including pilot testing, were adhered to and approved by the relevant institutional review board. This also applied to modifications in the research instruments and methodology. Three distinct pilot studies were executed before the final data collection. Comprehensive analyses and amendments resulting from each pilot test are documented in the associated endnotes. The pilot test with 50 participants aimed to validate the study's measures and experimental manipulations [124].[5] The main takeaway from Pilot 2 was confirmation of measurement validity, proper randomization (ensuring a balanced distribution of the four treatments), and manipulations (showing statistically significant differences in the theorized directions), along with the refinement of our measures and the inclusion of additional control variables. See Endnote 6 for more details.

Following enhancements derived from this pilot, a second test with another set of 50 respondents was conducted.[6] In Pilot 2, the refined measures (i.e., previously validated multi-item scales that were trimmed down and improved across pilots) were used; they all showed excellent reliability. See Endnote 6 for more details on this. The online instrument was also optimized (e.g., by moving specific questions closer to the video vignettes in the online survey), and a manipulation check was conducted using the refined measures, which confirmed its success. For more details, see Endnote 7. Subsequent improvements led to the third pilot, which replicated the study procedures with 52 participants.[7] In Pilot 3, all measures were refined, and reliability and validity were assessed. Potential survey fatigue was addressed by optimizing the overall length of our questionnaire. For more details, see Endnote 8. These three pilot studies, executed via Prolific Academic, substantiated the effectiveness and validity of the experimental manipulations, methodologies, and instruments.

Treatments

A 2 × 2 between-subjects online experiment featured two distinct levels of stigmatization—" high" for schizophrenia and "low" for attention-deficit/hyperactivity disorder (ADHD)—across two therapy modalities (face-to-face and remote). The reason behind choosing these specific disorders to model different levels of stigma was that conditions like schizophrenia and ADHD are among the most prevalent

mental health disorders. Yet, they occupy distinctly different positions on the stigmatization spectrum. Schizophrenia is often heavily stigmatized, whereas ADHD tends to be less so [24, 70].

We randomly assigned the participants to watch one of four video vignettes, each portraying either a virtual (remote) or an in-person (face-to-face) mental health counseling session between a psychiatrist and a patient.[8] Professional actors were hired to create these vignettes. Additionally, the person acting as the mental health provider is a practicing therapist with real-world experience in online therapy. This, in turn, enhanced the ecological validity of the video vignettes, thereby positively influencing the overall realism of the study. Support roles were filled by students who participated voluntarily without monetary incentives. The vignettes depicted patients exhibiting symptoms of either schizophrenia or ADHD, crafted in adherence to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) standards, ensuring diagnostic accuracy. A practicing therapist reviewed and endorsed all four vignettes, confirming their realism and ecological validity. Each mental health condition was portrayed in face-to-face and remote session formats, with the VSee platform serving as an exemplar of online videoconferencing services. **Figure 4** shows screenshots of the in-person and remote video vignettes.

Figure 4. Screenshot of Video Vignettes

Virtual (Remote) Session	In-Person (Face-to-Face) Session

Critical considerations in telehealth, such as HIPAA[9] compliance, confidentiality, trust, audio and video quality, and the reliance on visual cues for rapport and empathy, were integral to this study [72, 74, 80]. VSee was selected for its alignment with these criteria, enhancing the study's ecological validity and effectively representing the technological aspects. VSee is a reputable telehealth service provider that offers secure, encrypted audio and video communication and HIPAA compliance. It also guarantees the security

of patient information by immediately reporting any breaches.

Task

In this study, participants viewed one of several video vignettes depicting either a face-to-face or virtual session between a psychiatrist and a patient displaying symptoms of either schizophrenia or ADHD. Following the Diagnostic and Statistical Manual of Mental Disorders (5th edition), we meticulously crafted these vignettes to reflect actual therapy sessions accurately. A licensed therapist with expertise in virtual consultations reviewed the scenarios for logical consistency and realism. Another experienced licensed therapist further corroborated the ecological validity of these vignettes.

Vignettes are a widely acknowledged research tool in examining trust attitudes and behaviors toward individuals and technologies [48, 121]. They are particularly powerful in technological contexts where social desirability bias or privacy concerns might skew responses about human interactions [39, 94, 133]. Research also indicates that video vignettes can elicit attitudes akin to those triggered by direct participation in the depicted scenarios [121]. Several meta-analyses have also demonstrated a high degree of concordance between outcomes from vignette-based studies and actual human behavior studies, albeit with marginally smaller effect sizes in the former [35, 121]. This underlines the efficacy of vignettes in simulating real-world contexts within a controlled experimental framework.

Participants

Following the initial pilot tests, the primary experiment collected data from 334 individuals through Prolific Academic, a panel data service. Data integrity was maintained through established protocols [93, 122]. Participation was voluntary, and the survey incorporated several attention checks to validate response authenticity. Fifteen partial submissions were excluded due to missing data. Additionally, 10 participants were disqualified for failing one or more attention checks. This rigorous screening process culminated in 309 analyzable responses.

The demographic composition of the final sample was diverse: 52.8% female, 77% white, 12% black, 6% Asian, and 4.5% “other.” The age distribution ranged from 18 to 82 years, with a mean age of 46 (standard deviation = 16.09). The predominant household income bracket was $25K-$50K. Educational

backgrounds varied as follows: 1.9% high school not completed, 28.5% high school diploma, 15.2% associate's degree, 37.5% bachelor's degree, 14.6% master's degree, and 2.3% doctoral degree.

Regarding mental health experiences, 53% of participants reported personal mental health issues, and 68% had loved ones with such experiences. Conversely, 24% indicated no direct or indirect experience with mental health concerns. Thus, the study reflected the broad spectrum of people seeking mental health support. This is particularly relevant in the context of the COVID-19 pandemic, which has underscored the need for mental health services across various populations [84]. Although the sample broadly represented the target population, analyses were adjusted for variations in prior mental health experience.

Measures

Construct validity was ensured by adopting established constructs from prior research and utilizing validated scales where feasible. To align with our specific context, minor modifications were made to some items. All constructs in this investigation were reflective, and measurement was via a variety of scales. These included 7-point Likert scales; 7-point, endpoint-anchored semantic differential scales; and binary yes/no scales.

The primary IV, antecedent disclosure goals, was assessed through participant ratings on an eight-item scale to gauge disclosure goals, acknowledging that disclosure is inherently goal-directed [108]. In stigmatized conditions, where self-disclosure may cause shame or embarrassment, *information disclosure* is formally defined as the verbal conveyance of self-relevant data, encompassing individuals' thoughts, feelings, and experiences [40]. In such contexts, the influence of antecedent disclosure goals is also significant, as these pre-existing intentions have been shown to shape individuals' decisions to share information in various settings [19, 20]. *Disclosure goals* are the initial intentions influencing the likelihood of disclosing information in a given situation. This scale comprised four items for approach-focused and four items for avoidance-focused goals. To capture the nuanced coexistence of approach- and avoidance-focused goals in individuals, these eight items were combined into a single continuous variable by averaging the approach-focused items and subtracting the avoidance-focused items. This method, which favors continuous over binary variables, aligns with approaches in disciplines such as toxicology and

pharmacology to achieve more accurate estimation [85].

Reflective measures were employed to determine the perceived stigma level associated with ADHD or schizophrenia [68]. Participants were asked to indicate the extent to which they thought stigma and negative connotations were associated with ADHD and schizophrenia. Established metrics were utilized to measure SPIR as a predictor [125], trust in technology as the mediating variable [102], and the intention to disclose stigmatized information as the DV [7]. For SPIR, participants were asked to indicate how personal/impersonal and cold/warm the therapy session was, and how sociable/unsociable and sensitive/insensitive they found the therapist to be. To assess trust in technology, they were asked to rate how well the VSee videoconferencing platform has the technological structures and safeguards (e.g., data encryption) to make them feel safe and comfortable using it for a virtual therapy session.

Data on the same construct were collected across all four treatments. For face-to-face (F2F) scenarios, participants were instructed to imagine themselves as the patient in a remote/virtual therapy session on the VSee platform, with a brief description of the platform provided. Except for the inclusion of "imagine," all information provided to subjects was identical across treatments. This uniformity strengthens the robustness of our analysis, especially regarding the trust-in-technology construct, for which data were gathered from all 309 participants.

Control variables included public stigma, treatment stigma, self-stigma, trust in doctors, disposition to trust and distrust, general privacy concerns, personal innovativeness with IT (PIIT), direct and indirect experiences with mental health issues, and demographic factors (age, gender, income, race, and education). These controls were integrated into the research model to mitigate confounding influences, address endogeneity concerns, and reinforce internal validity. **Table 1** summarizes our measures and controls, which are detailed in **Appendix A.**

Results of Analysis

To maximize the robustness and rigor of our empirical analyses, we took a multi-stage approach and conducted comprehensive tests. We started by (1) validating the experimental treatments and manipulation checks to ensure the success of our experiment as a whole, (2) continued with establishing model fit,

instrument validity, and testing for different potential biases, (3) culminating in a detailed report of our research hypotheses testing, and finally (4) provided the results of our post hoc robustness analyses.

Validating the Experimental Treatments and Manipulation Checks

To ensure that treatments were valid and the choice of data analysis procedures was an optimal fit for the research questions, the following steps were taken: (1) a randomization and normality check, (2) instrument validation, (3) manipulation checks, and (4) a mapping of subjects' perceptions of the nature of their

Table 1. Summary of Measures, Manipulations, and Controls

Construct	Manipulated or Measured	Model Variable Type	Source
ADHD/Schizophrenia-related stigma	Manipulated & measured manipulation check	Moderator/Exogenous	Hatzenbuehler et al. [68]
Antecedent disclosure goals	Measured	Exogenous	Chaudoir and Fisher [19]
Direct experience with mental health concerns	Measured	Control	n/a
Disposition to distrust	Measured	Control	Everard and Galletta [49]
Disposition to trust	Measured	Control	Gefen [55]
General privacy concerns	Measured	Control	Culnan [37]
Indirect experience with mental health concerns	Measured	Control	n/a
Intention to disclose	Measured	Endogenous	Anderson and Agarwal [7]
PIIT	Measured	Control	Culnan [37]
SPIR	Manipulated & measured manipulation check	Exogenous	Straub [125]
Public stigma	Measured	Control	Kanter et al. [79]
Self-stigma	Measured	Control	Kanter et al. [79]
Social desirability	Measured	Social desirability check	Anderson and Agarwal [7]
Treatment stigma	Measured	Control	Kanter et al. [79]
Trust in technology	Measured	Mediator/Endogenous	McKnight et al. [102]
Trust in the doctor	Measured	Control	Anderson and Dedrick [8]
Age	Measured	Control	n/a
Gender	Measured	Control	n/a
Race	Measured	Control	n/a
Education	Measured	Control	n/a

Note: PIIT = personal innovativeness with IT; SPIR = social presence and information richness.

treatments to the group assignments. **Table 2** summarizes treatments, experimental manipulations, and sample sizes of randomly assigned groups.

Table 2. Experimental Design and Treatment Distribution (n = 309)

	Face-to-Face	Virtual/Remote	Total
High Stigma	Face-to-Face Schizophrenia (n = 65)	Virtual Schizophrenia (n = 88)	n = 153
Low Stigma	Face-to-Face	Virtual	

	ADHD (n = 91)	Schizophrenia (n = 65)	n = 156
Total	n = 156	n = 153	n = 309

Randomization and Normality Check

In this study, an online experiment with random assignment to different treatments was employed, a strategy effective in controlling for pre-treatment disparities among participants [119]. A categorical variable with four categories was created to assess the effectiveness of randomization. Each category corresponded to a treatment group numerically labeled from 1 to 4 (see **Table 2**). This categorization, established before treatment administration, facilitated equivalence testing across groups.

We then conducted a Kolmogorov–Smirnov test to assess the normality of continuous variables, including the unmanipulated IV, the mediator, and the control variables. The results indicated that all these continuous variables were non-normal. We thus conducted a Kruskal–Wallis test, a nonparametric counterpart to the one-way analysis of variance (ANOVA), to evaluate significant differences in distribution across the four treatment groups and determine whether it was appropriate to run parametric tests like those in the ANOVA family, as **Table 3** details. For the nominal variables (identified with an asterisk), there was no violation of assumptions that would affect the running of a one-way ANOVA, a parametric equivalent to the Kruskal-Wallis test.

The analysis utilized the categorical "treatment" variables mentioned above to distinguish between the treatment groups. As **Table 3** indicates, the analysis revealed no significant statistical differences in pre-treatment group means across several measures: approach-focused goals, avoidance-focused goals, public stigma, treatment stigma, self-stigma, trust in doctors, disposition to distrust, general privacy concerns, PIIT, direct experience, indirect experience, as well as demographic factors such as age, gender, income, race, and education. Therefore, despite the non-normal distribution of the data, it remains appropriate to proceed with the experimental group testing [29].

Manipulation Checks

To verify the effectiveness of the manipulations, subjects were informed of the interaction medium (face-to-face or virtual). They were given an overview of the mental disorder just before viewing the video. This

approach was pivotal in ensuring subjects' comprehension of the interaction medium, the mental health condition presented, and the associated stigma level—fostering the manipulations' validity. Following the video vignette, participants were asked about their perceptions of these manipulations. This involved asking them about the medium of interaction and the specific mental disorder portrayed in the video. To ascertain their awareness of the treatments, we used two binary (yes/no) questions — one concerning the remote vs. face-to-face manipulation and the other addressing ADHD vs. schizophrenia manipulation. These questions tested perception and served as attention checks to eliminate invalid responses.

Table 3. Descriptive Statistics and Kruskal-Wallis Test Results for All 4 Treatments

	High Stigma Face-to-Face	**Low Stigma Face-to-Face**	**High Stigma Remote**	**Low Stigma Remote**	**Test Statistic**	**Asymptotic *p*-value**
Variable	1	2	3	4	Value	2-Sided
Approach-focused goals	4.67 (1.53)	4.47 (1.52)	4.56 (1.58)	4.55 (1.70)	1.31	0.77
Avoidance-focused goals	4.58 (1.45)	4.65 (1.30)	4.55 (1.47)	4.40 (1.56)	0.45	0.93
Public stigma	1.56 (1.02)	1.67 (0.93)	1.77 (0.96)	1.66 (0.91)	3.88	0.28
Treatment stigma	4.57 (1.37)	4.75 (0.99)	4.52 (1.14)	4.72 (1.06)	3.12	0.37
Self-stigma	4.50 (1.55)	4.60 (1.20)	4.39 (1.25)	4.49 (1.35)	1.96	0.58
Trust in doctors	4.89 (1.30)	5.01 (1.07)	4.70 (1.08)	5.01 (1.13)	5.30	0.15
Disposition to trust	5.22 (0.88)	4.68 (0.90)	4.84 (1.00)	4.76 (1.13)	12.45	0.01
Disposition to distrust	4.11 (1.41)	4.12 (1.42)	4.17 (1.28)	3.99 (1.48)	3.82	0.28
General privacy concerns	4.99 (1.34)	4.83 (1.45)	4.66 (1.36)	4.64 (1.50)	2.62	0.45
PIIT	4.70 (1.37)	4.40 (1.48)	4.74 (1.52)	4.59 (1.68)	2.56	0.46
Direct experience*	56.90%	50.50%	53.40%	53.80%	0.36	0.79
Indirect experience*	63.10%	67.00%	75.00%	64.60%	1.17	0.32
Age	47.37 (16.32)	45.43 (15.84)	43.95 (16.82)	48.34 (15.12)	3.80	0.28
Gender (Female)*	64.60%	59.30%	44.30%	43.10%	1.81	0.15
Income: < $25K*	10.80%	19.80%	19.30%	23.10%	1.21	0.31
$25K–$49.9K*	27.70%	23.10%	31.80%	29.20%	0.59	0.62
$50K–$74.9K*	21.50%	17.60%	15.90%	18.50%	0.27	0.85
$75K–$99.9K*	7.70%	14.30%	20.50%	10.80%	1.94	0.12
$100K–$149.9K*	20.00%	16.50%	6.80%	13.80%	2.09	0.10
$150K–$200K*	7.70%	6.60%	2.30%	0.00%	2.33	0.08
> $200K*	4.60%	2.20%	3.40%	4.60%	0.30	0.82
Race: White*	76.90%	72.50%	76.10%	86.20%	1.39	0.25
Black*	12.30%	18.70%	8.00%	9.20%	1.86	0.14
Asian*	3.10%	6.60%	10.20%	1.50%	2.11	0.10
Other*	4.60%	2.20%	4.50%	3.10%	1.08	0.36
Education: < High school*	1.50%	2.20%	0.00%	4.60%	1.42	0.24
High school diploma*	26.20%	29.70%	29.50%	27.70%	0.10	0.96
Associate degree*	18.50%	16.50%	15.90%	9.20%	0.82	0.48
Bachelor's degree*	33.80%	39.60%	39.80%	35.40%	0.28	0.84
Master's degree*	20.00%	7.70%	13.60%	20.00%	2.22	0.09
Doctoral degree*	0.00%	4.40%	1.10%	3.10%	1.36	0.26
n	65	91	88	65	309	309

Note: Direct Experience and Indirect Experience are self-experience and loved ones' experiences with mental health issues, respectively. A Kruskal-Wallis test was conducted for all four treatments. In the four treatment columns, the first number is the mean, and the one in parentheses is the standard deviation. For the binary and categorical variables, the frequency percentages are shown. PIIT = personal innovativeness with IT.

The *t*-tests confirmed that the manipulations were effective. The variables of interest in these tests were

SPIR and the stigma related to either ADHD or schizophrenia, corresponding to the remote vs. face-to-face and ADHD vs. schizophrenia treatment groups, respectively. **Appendix A** details the four-item reflective measures to assess stigma. **Table 4** shows the results of these manipulation *t*-tests, demonstrating significant differences ($\alpha = 0.05$) for both the remote vs. face-to-face and ADHD vs. schizophrenia manipulations.

Mapping of Subject Perceptions to Group Assignments

Previous research has established that stigma and SPIR evoke complex psychosocial responses [22, 30, 67, 125]. Recognizing that broad categorizations might not fully capture these complexities, we enhanced our analysis of experimental blocks and group assignments by measuring participants' reactions to the treatments using multi-item latent variables. This approach, capable of capturing a broader range of variance and subtleties inherent to these constructs, aligns with methodologies commonly used in sensitive research areas such as pharmacology and toxicology, where even minor variations are critical [85]. The sensitivity of mental health topics and the precision required in interpreting results in this domain make this method particularly suitable. Advantages of this approach include more straightforward interpretation of results, increased statistical power due to more accurate estimates, and the flexibility to transform the predictor variable if necessary [85]. **Appendix C** provides further explanations and theoretical and empirical justifications for these choices.

Table 4. Manipulation Checks

Manipulation (Construct)	n	Mean	SD	SE	*t*	df	*p*-value 2-Tailed	Mean Difference	Cohen's *d*
Remote vs. F2F (SPIR)	156	5.28	1.17	0.09					
	153	4.96	1.03	0.08	2.56	307	.01	0.32	1.10
ADHD vs. Schiz. (Stigma)	153	4.46	0.86	0.07					
	156	3.50	0.91	0.07	9.57	307	< .01	0.96	1.09

Note: for n, mean, and standard deviation, the top numbers represent the treatments "Face-to-Face" and "Schizophrenia", depending on the cells; the bottom numbers represent the treatments "Remote" and "ADHD", depending on the cells. df = degrees of freedom. Schiz. = schizophrenia treatment; SD = standard deviation; SE = standard error; stigma = perceived ADHD/schizophrenia-related stigma construct; SPIR = social presence and information richness.

We used binary logistic regressions to ascertain the effectiveness of these measures in reflecting the assigned experimental conditions. These regressions (1) correlated the measured variables with the binary treatment levels and (2) verified that these variables significantly predicted the assigned binary groups. **Table 5** provides results confirming that all perceptual measures effectively corresponded to the binary

treatment variables. Thus, these measures can be regarded as both statistically significant and reliable proxies for the treatments.

Table 5. Binary Logistic Regression Results

Manipulation (Construct)	ß	SE	Wald	df	*p*-value	Exp (ß)
Remote vs. F2F (SPIR)	-0.27	0.11	6.30	1	0.01	0.77
ADHD vs. Schiz. (Stigma)	-1.22	0.16	56.57	1	< 0.01	0.29

Note: F2F = face-to-face treatment; schiz. = schizophrenia treatment; SE = standard error; stigma = the perceived ADHD/schizophrenia-related stigma; SPIR = social presence and information richness; Wald = Wald statistic; β = beta coefficient.

Model Fit and Instrument Validity

A confirmatory factor analysis (CFA) evaluated the initial model fit before the final data analysis. The CFA included a range of pre-analyses to assess construct validity and reliability and to ensure the absence of multicollinearity, nonresponse bias, common-method bias, and social desirability bias. The model demonstrated excellent fit, indicated by several metrics: CMIN/DF = 1.930 (ideal range: 1–3), SRMR = 0.057 (threshold: < 0.08), RMSEA = 0.055 (threshold: < 0.06), and CFI = 0.922 (criteria: > 0.95 = excellent, 0.90–0.95 = acceptable). These results align with recommended research benchmarks [57, 77].

Establishing Construct Validity

Construct validity was confirmed through multiple criteria. First, all standardized factor loadings were above 0.50 and significant, with each item displaying higher loading on its intended construct than on any other (**Table B.2**). This outcome indicates strong convergent and discriminant validity [63]. A Pearson's correlation matrix, encompassing all constructs and control variables, revealed that the square root of the average variance extracted (AVE) for each latent variable exceeded its correlations with other latent variables. These findings satisfy the Fornell-Larcker criterion for acceptable convergent validity [52]. Discriminant validity was also evaluated using the heterotrait–monotrait (HTMT) ratio of correlations, with all HTMT values falling below the recommended 0.85 threshold [73]. Detailed HTMM results are excluded here due to space constraints, but are available upon request.

Establishing Reliability and Acceptable Levels of Multicollinearity

All constructs met the reliability standard, with Cronbach's alpha values and composite reliability scores exceeding the recommended threshold of 0.70 [52, 73]. **Figure 3** illustrates the role of stigma as a moderating variable. To mitigate multicollinearity concerns, especially when creating an interaction term

between stigma levels and disclosure goals, both constructs were mean-centered, as suggested by [69]. Additionally, each construct's variance inflation factors (VIFs) were calculated, revealing all values below the maximum recommended level of 3.30, indicating a lack of multicollinearity issues [112]. **Appendix B** provides further details on construct validity, reliability, and multicollinearity.

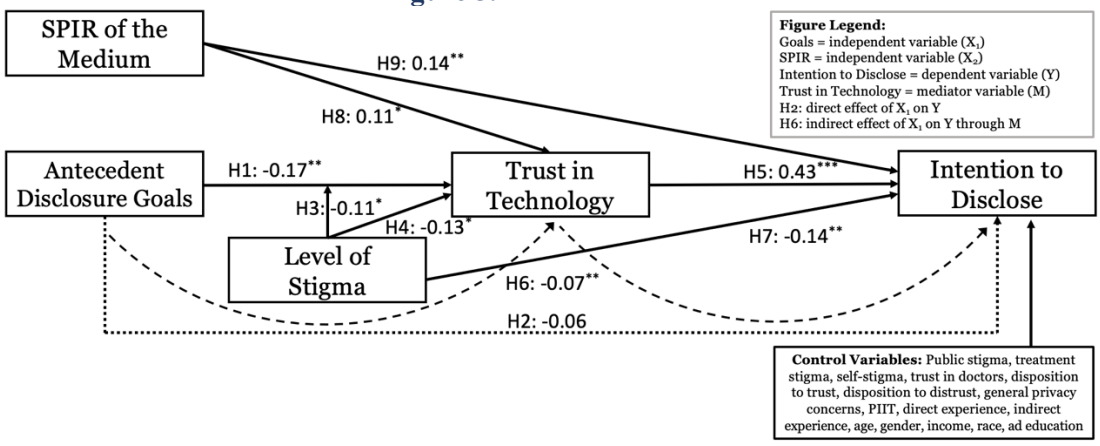
Testing for Different Biases

Next, nonresponse bias, common method bias, and social desirability bias were examined. **Appendices B3** and **B4** provide the details of these tests, confirming that none of these biases is a concern.

Test of Research Hypotheses

We tested the model in **Figure 5** using covariance-based structural equation modeling (CB-SEM) via SPSS AMOS version 27, following the latest established standards of analysis [54]. CB-SEM was chosen for its ability to model constructs grounded in well-established theoretical bases, to account for measurement errors in its estimates, and to use multiple items [57]. Notably, some continuous variables deviated from normal distributions. Bootstrapping was employed, given the inclusion of estimates [29]. **Figure 5** depicts the main, mediation, and moderation effects alongside covariates, which were assessed using 5,000 bootstrap resamples, and **Table 6** provides the details. The model fit was strong, as indicated by CMIN/DF = 1.031, CFI = 0.999, and RMSEA = 0.010. The structural model's explanatory power (R^2) revealed medium and large effect sizes for trust in technology and intention to disclose, with explained variances of 0.30 and 0.45, respectively [27]. **Table 7** summarizes these findings, including the results of hypothesis testing.

Figure 5. Structural Model Results



Note: n = 309. Level of stigma represents the perceived ADHD/schizophrenia-related stigma construct. Two-tailed tests were conducted for variable coefficients. *** significant at 0.001; ** significant at 0.01; * significant at 0.05; † significant at 0.10. The

standardized estimates are reported. All variables that define interaction terms have been mean-centered.

Analysis of the data presented in **Table 6** and synthesized in **Table 7** confirmed all proposed hypotheses except H2. This exception denotes a significant boundary condition within the DPM framework, highlighting the non-significance of the direct path from antecedent goals to the intention to disclose stigmatized information in online environments.

As part of the hypothesis testing, interactions were examined in which stigma level moderated the effect of antecedent goals on trust in technology. The interaction between stigma level and antecedent goals was

Table 6. Estimated Relationships of the Structural Model

Variable	TT	*p*-value	ITD	*p*-value
Antecedent goals	-0.17**	0.002	-0.06	0.197
Trust in technology	—	—	0.43***	< 0.001
Goals → TT → ITD	—	—	-0.07**	0.004
StigmaAS	-0.13*	0.013	-0.14**	0.002
Goals × StigmaAS	-0.11*	0.030	—	—
SPIR	0.11*	0.050	0.14**	0.007
Public stigma	0.00	0.999	-0.02	0.667
Treatment stigma	0.04	0.553	0.10	0.123
Self-stigma	-0.09	0.195	-0.02	0.773
Trust in doctors	0.33***	< 0.001	0.15**	0.004
Disposition to trust	0.13*	0.027	0.12*	0.027
Disposition to distrust	0.13*	0.021	-0.04	0.407
General privacy concerns	-0.19***	< 0.001	0.04	0.400
PIIT	0.12*	0.026	0.03	0.480
Direct experience	0.00	0.991	-0.05	0.317
Indirect experience	0.03	0.621	-0.07	0.178
Age	0.00	0.957	0.10*	0.032
Female	0.00	0.995	-0.03	0.575
Income: < $25K	-0.09	0.136	-0.03	0.631
$50K–74.9K	-0.15*	0.011	0.05	0.395
$75K–$99.9K	0.01	0.930	0.04	0.437
$100K–$149.9K	-0.05	0.428	0.00	0.986
$150K–$200K	-0.01	0.823	-0.08†	0.096
>$200K	-0.04	0.401	0.07	0.127
Race: Black	0.08	0.123	-0.02	0.698
Asian	0.03	0.621	-0.03	0.532
Other	0.00	0.986	0.00	0.974
Education: < HS	-0.01	0.830	-0.07	0.140
High school diploma	-0.03	0.572	-0.07	0.208
Associate degree	0.00	0.978	-0.02	0.684
Master's degree	0.05	0.386	-0.07	0.138
Doctoral degree	0.11*	0.039	0.07	0.143
R^2	0.30	—	0.45	—

Note: n = 309. *** significant at 0.001; ** significant at 0.01; * significant at 0.05; † significant at 0.10. The standardized estimates are reported in the table. Goals → TT → ITD represents the mediation effect (i.e., the indirect effect of antecedent goals on intention to disclose through trust in technology). For gender, male was the benchmark; for race, white was the benchmark; for income, the category $25K−$49.9K; and for education, a bachelor's degree was the benchmark. ITD = intention to disclose; PIIT = personal innovativeness with IT; TT = trust in technology.

Table 7. Summary of Hypotheses Testing Results

Hypothesis Summary	Support?
H1. Avoidance-dominated goals → (-) trust in platform	Yes
H2. Avoidance-dominated goals → (-) intention to disclose	No
H3. Stigma negatively moderates disclosure goals → trust in the platform	Yes
H4. Stigma → (-) trust in the platform	Yes
H5. Trust in platform → intention to disclose	Yes
H6. Antecedent disclosure goals → trust in the platform [mediator] → intention to disclose	Yes
H7. Stigma → (-) intention to disclose	Yes
H8. SPIR → trust in platform	Yes
H9. SPIR → intention to disclose	Yes

negative, as expected, and significant, thereby supporting H3. **Table 8** summarizes the results, indicating that antecedent goals had a more substantial effect on trust in technology when stigma was higher.

Table 8. Moderation Effects of Stigma on Trust in Technology

Level of ADHD/Schizophrenia-Related Stigma	Estimate	Lower	Upper	*p*-value
Low (Mean – 1 standard deviation)	-0.900	-0.272	0.101	0.455
Medium (Mean)	-0.245	-0.385	-0.093	0.006
High (Mean + 1 standard deviation)	-0.400	-0.635	-0.184	0.002

Note: 5000 bootstrap samples were drawn. "Lower" and "upper" represent the lower and upper bounds of the bootstrapped confidence interval, respectively.

A comprehensive sequence of analyses was executed to confirm full mediation. Despite some criticisms in the literature about the rigid assumptions of Baron and Kenny's method [11, 133, 145], it remains a widely recognized approach for establishing full mediation [47, 76]. The present analytical approach adhered stringently to their guidelines. **Table 9** shows that the direct paths from antecedent goals to the intention to disclose information and trust in technology were significant. This confirms the successful completion of the first two steps of the Baron and Kenny method.

In subsequent stages of our analysis, trust in technology, the mediating variable, significantly predicted patients' intention to disclose information, even after controlling for antecedent goals. Notably, the direct path between antecedent goals and intention to disclose became non-significant when accounting for

Table 9. Testing for Full Mediation of Trust in Technology

Path	Estimate	*p*-value	B&K Step	Successful?
Goals → ITD	-0.282***	< 0.001	1	Yes
Goals → TT	-0.119*	0.013	2	Yes
TT → ITD (controlling for goals)	-0.435***	< 0.001	3	Yes
Goals → ITD (controlling for TT)	-0.073	0.162	4	Yes

Note: All covariates appearing in Table 9 were controlled for in all the above analyses. B&K = key step in Baron and Kenny's approach; goals = antecedent disclosure goals; ITD = intention to disclose; TT = trust in technology.

trust in technology. This outcome validates the fulfillment of steps three and four of the Baron and Kenny

approach. The results detailed in **Table 9** verify the full mediation effect of trust in technology in the relationship between antecedent goals and the intention to disclose information. This finding robustly supports H6.

Post Hoc Robustness Analyses

The presence of social desirability bias in our study was indicated by a chi-square difference test, as previously noted. To assess the robustness of our findings, we recalibrated measures to account for social desirability bias by including a control variable in the TIDM. The revised model demonstrated exceptional fit (CFI = 1.000, RMSEA = 0.000). The explanatory power of the structural model, indicated by the coefficient of determination (R^2), was substantial, at 0.46 for trust in the technological platform and 0.51 for intention to disclose. These results closely mirrored those obtained with the original structural model. Detailed results are available in **Table B.5**. As a further robustness check, the Hayes PROCESS Model 8, an ordinary least squares regression method, was applied to the same dataset. This model aligns closely with our structural model and encompasses all relationships estimated in our CB-SEM analysis. To maximize congruence with the executed CB-SEM procedures, 5,000 bootstrap resamples were generated, and all continuous variables involved in product terms were mean-centered. The variances between trust in technology and intention to disclose were 0.30 and 0.45, respectively. These findings were nearly identical to our initial AMOS results, further reinforcing the robustness of our outcomes (see **Table B.6**).

Discussion

The escalating mental health crisis presents significant global challenges. Key among these are stigmatization and limited access to effective treatment solutions. When deployed optimally, telehealth can diminish these barriers, facilitating improved mental health outcomes. A critical element in accessing mental health care online is the initial disclosure of information, a process influenced significantly by the communication medium. The current study provides valuable insights for academics and practitioners on the differences between face-to-face and online (IT-enabled) patient-provider communication in promoting the disclosure of sensitive, stigmatized information.

We studied how perceived social presence and information richness, as instantiated in our experimental

design, affect disclosure. This research demonstrates that the stigma associated with mental health issues can be alleviated through telehealth solutions, particularly when the medium of communication possesses high levels of SPIR. Online platforms, including videoconferencing, increase the likelihood that patients will disclose their conditions to healthcare providers. This effect is consistent across various patient goal conditions, highlighting that higher perceived social presence and information richness can enhance patients' trust in the technology used for healthcare interactions. Whereas trust in the healthcare provider is essential, the technological medium also plays a crucial role in fostering trust.

To explore this phenomenon, the DPM adapted it into a newly proposed TIDM, specifically tailoring it to the context of telehealth. This model examines the decision-making process patients undergo when contemplating the online disclosure of stigmatized conditions, such as ADHD or schizophrenia. It considers the interplay between antecedent disclosure goals, the stigma associated with mental health issues, trust in technology, SPIR of the communication medium, and the intent to disclose sensitive personal information. The model illuminates how SPIR (unique to each communication medium) influences the relationship between antecedent goals and disclosure, pinpointing the mediating role of trust in technology and the moderating impact of perceived disease-specific stigma.

Empirically validating the TIDM involved collecting data from 309 participants through Prolific Academic. The findings reveal that perceived SPIR and the degree of stigma significantly predict trust in technology and the intention to disclose private information. Notably, we did not manipulate specific design features across multiple platforms (with varying levels of social presence and information richness); therefore, our findings about SPIR should be viewed as theoretical advancements on the perceived SPIR of the communication medium, rather than causal empirical claims about IT platforms' interface design features. We also found that stigma level moderates the relationship between antecedent goals and trust in technology. As stigma severity increases, the negative relationship between these factors intensifies, underscoring the nuanced interdependencies within telehealth contexts.

Contributions to Research and Theory

Table 10 summarizes the contributions of this research that intersect multiple disciplines, including online

information self-disclosure, stigma, and telehealth. The contributions enrich the broader discourse on leveraging IT platforms and telemedicine to mitigate the stigmatization barriers inhibiting mental health disclosures and treatment-seeking behaviors. Research on self-disclosure in online environments is extensive, but studies in stigmatized contexts are rare [5, 116], highlighting a critical gap. The role of various communication modes in fostering user comfort and disclosure is also underexplored. Although some studies identify factors influencing digital health disclosure [59], evidence from telemental health suggests technological features can cause discomfort, underscoring the need for research on the impact of different characteristics of the mode of communication on self-disclosure in stigmatized settings [23].

Table 10. Summary of Contributions and Implications

Prior Literature	This Study's Approach	Contributions and Implications
Despite substantial work on information disclosure, IS research on digital health disclosure has not examined stigma–disclosure relationships, and no prior studies have used a stigma-informed theory (e.g., DPM).	Introduces the DPM and contextualizes it.	• Extends IS disclosure research by integrating stigma as a core contextual factor. • Applies DPM to explain online information self-disclosure in stigmatized contexts. • Develops a middle-range theory for online disclosure. • Extends a formal theory to technology-enabled contexts.
Despite significant prior work on disclosure in digital healthcare, prior work lacks a focused examination of stigma's effects on antecedent goals, trust in technology, and online disclosure.	Embeds stigma in the online information disclosure equation and examines its causal effects via an experimental approach.	• • Theorizes and empirically validates stigma's role in predicting trust in technology. • Identifies stigma's adverse moderating effect on the goal → trust path. • Provides conceptualization and measurement of stigma for IS research.
Despite extensive work on social presence and information richness, the prior literature lacks a limited evaluation of SPIR as an antecedent of disclosure in stigmatized contexts.	Introduces SPIR in the online information disclosure equation in a stigmatized setting.	• Extends prior work in IS and trust research by confirming that SPIR predicts trust in technology and online information disclosure in stigmatized contexts, like other (non-stigmatized and previously tested) contexts.
Despite substantial work on disclosure goals and information disclosure in the psychology and IS literatures, there are no prior examinations of disclosure goals as antecedents of trust in technology or of *online* information self-disclosure.	Examines the role of antecedent goals in predicting trust in technology and in online information disclosure, and defines the essential underlying mechanisms and boundary conditions.	• Enriches the telehealth and information self-disclosure literature by delineating the role of trust in the IT artifact as a mediating factor in online settings (via theorizing and empirically validating this causal path). • Defines a vital boundary condition of the DPM, showing that the direct effect of antecedent goals on information disclosure (present in the original theory) does not hold in our online setting and requires trust in technology as a mediating mechanism. • Enriches the literature by showing that antecedent goals can predict trust in technology and online information disclosure. • Although telehealth platforms can have varying degrees

		of social presence and richness, and a direct comparison between "in-person" and "remote" may not fully capture the IT system's specific design influences, given the statistically significant difference of SPIR found between these two means of communication, our results identify **SPIR differences** between in-person and remote communication, offering **design insights** on desirable communication characteristics (social presence, information richness) and informing **telehealth practitioners** about **patient factors** influencing stigmatized self-disclosure online.
Limited analysis of the effects of communication medium characteristics (e.g., SPIR) on disclosure in stigmatized settings.	Evaluates communication medium characteristics affecting disclosure.	• Informs scholars and practitioners about communication characteristics encouraging people to disclose stigmatized information. • Supports the use of **IT and telemedicine** to **reduce stigma-related barriers** to mental health **disclosure and help-seeking**.

Our study bridges key gaps by contextualizing the DPM. This relatively new grand theory consolidates decades of research about information self-disclosure in stigmatized areas, including mental health and telemedicine, extending its relevance to technology-enabled environments [75]. Factors such as trust in the IT artifact and the perceived social presence and information richness of the communication medium (SPIR) are proposed to enhance the explanatory power of the DPM in online disclosure contexts. This adaptation introduces a novel middle-range theory, balancing abstraction with empirical grounding to enable generalizations and actionable insights while fostering innovative theorizing beyond repetitive variable rearrangements in information systems research [65, 66].

The pivotal theoretical advancement is TIDM, a middle-range model evolving from the recontextualization of the DPM. TIDM is tailored to examine the decision-making process of mental health patients with varying levels of perceived disease-specific stigma in their deliberation to disclose conditions to telehealth providers. It integrates factors like perceived stigma, SPIR, trust in technology, and antecedent goals for information disclosure.

A randomized, controlled experimental design allowed for novel causal claims within the TIDM framework, thereby challenging some foundational assumptions of the DPM. Contrary to the DPM's assertion of a direct link between antecedent disclosure goals and disclosure intention, our findings in an online context reveal that trust in technology fully mediates this relationship. This discovery refines the

DPM in two significant ways: first, by identifying an unexplored causal pathway that illuminates patient information disclosure in telehealth environments; second, by establishing a critical boundary condition for applying the DPM in telehealth contexts: the online medium disrupts the direct connection between antecedent disclosure goals and disclosure intention.

Although prior IS models of trust and self-disclosure in digital health, such as those grounded in privacy calculus, privacy boundary theory, APCO, TAM, adoption-oriented trust models, or RFT, have offered valuable insights into user adoption and risk-benefit evaluations, they often treat disclosure decisions as relatively static and utility-driven [4, 7, 131, 135, 140]. In contrast, TIDM provides a more dynamic, context-sensitive lens by foregrounding how users cognitively process disclosure decisions within stigmatized telehealth settings. Specifically, our work extends existing IS literature by integrating the role of perceived disease-specific stigma and platform characteristic cues into the disclosure process — factors typically under- or unexplored in mainstream IS adoption models. Earlier studies emphasize generalized notions of trust or privacy concerns; however, our model delineates how situational factors, such as the characteristics of the communication medium and antecedent disclosure goals, interact with trust in technology to shape disclosure behavior. In doing so, we advance a more granular understanding of disclosure that moves beyond traditional models of technology acceptance, trust, and privacy research and adds explanatory power in sensitive health contexts such as mental healthcare.

This research also reveals that avoidance-focused attitudes shape disclosure goals in telehealth settings without active manipulation. We also present novel insights into the role of stigma, demonstrating its direct negative impact on online disclosure intentions and trust in technology and its moderating effect on the relationship between antecedent disclosure goals and trust in technology. These findings make significant strides in the theoretical and practical understanding of stigma within telehealth contexts.

The study also confirms a direct link between SPIR and vital elements of disclosure intentions and trust in technology. We must note that we treated perceived social presence and information richness cues as key differentiating factors between online and offline communication. However, we did not examine SPIR levels across multiple online platforms. Because telehealth platforms can vary in social presence and

information richness, a direct comparison between "in-person" and "remote" options may not fully capture the IT system's specific design influences. This is an important limitation and external validity boundary for our study insights. These insights provide a foundational baseline for future research, particularly in high-risk or highly sensitive disclosure scenarios within the telehealth, privacy, and security domains. Subsequent studies could further explore the dynamics of approach- or avoidance-focused goals, use social presence and information richness as a baseline and high-level characteristics of the communication medium, and look into more granular design options that are high or low along either one of these key factors, and investigate their broader implications in these domains.

Implications for Practice and Society

The theoretical insights and empirical evidence presented in this study hold substantial practical and societal implications, particularly if they hold in future empirical research and similar contexts. This importance stems from the role of information disclosure as a fundamental step in accessing mental health treatment. Enhanced disclosure of stigmatized mental health conditions to professional online providers correlates with improved access to adequate care. This, in turn, leads to significant personal and societal benefits. These benefits range from enhanced interpersonal relationships to broader impacts like increased job stability, reduced incidents of suicide and violence, decreased occurrences of broken homes and child abuse, elevated work productivity, reduction in physical health comorbidities, and lowered medical system costs. Consequently, medical practice and society benefit when patients feel more comfortable disclosing their conditions via telehealth. Indeed, several other implications can be offered to practice and society. However, these benefits rely on several critical enablers of technological solutions—specifically, Internet access and the digital literacy of the target population. Addressing these obstacles may prove particularly challenging for certain groups, such as rural communities and underprivileged populations in developing countries. One potential solution could be to deploy comparable low-tech communication channels, such as text messages on cell phones, for remote therapy in regions where traditional care infrastructure is not readily available (and will not be in the foreseeable future).

Targeted therapeutic interventions: Mental health professionals can use these insights to tailor their

approaches, especially in telehealth settings, to encourage patient disclosure and more effectively address stigmatized conditions. For example, our findings indicate a dominant role of avoidance-focused attitudes over disclosure goals in the absence of manipulated approach- or avoidance-focused goals. Thus, actively promoting approach-focused goals, potentially through priming techniques, emerges as a vital strategy in telemedicine deployment to counter the negative impact of avoidance-focused goals on trust in technology.

Enhanced mental health support: Organizations can leverage telehealth platforms to provide more effective support to employees. Organizations can create supportive environments that encourage openness about mental health by understanding the factors influencing disclosure in telehealth settings. Given the global trend toward remote work, understanding how telehealth options affect disclosures of mental health is crucial. Organizations can use these insights to improve their remote work policies and systems, enhancing employee well-being.

Broadening access to mental health care: Our findings speak to improving the quality of early-session disclosure for patients who do access telemental health, particularly in stigmatized contexts. Ideally, by increasing the scalability, accessibility, and affordability of mental health services through telehealth, a broader population can receive necessary care. Nevertheless, access expansion depends on structural factors (e.g., coverage, devices, and broadband) beyond the scope of our study, and any access-related implications are indirect and contingent (e.g., reducing discomfort may lower drop-off at intake for some groups). Like those explored in this study, telehealth solutions offer critical benefits to patients without physical access to quality healthcare or the financial means to afford it. The pragmatic benefits of telemedicine and promoting online disclosure are manifold. Beyond stigma, many mental health patients face additional challenges like comorbidities, which reduce their motivation and ability to attend in-person appointments—sometimes necessitating legal intervention. Conversely, virtual appointments demand significantly less motivation and effort. Telehealth services are vital in regions with limited access to in-person care—whether in rural or urban settings—where challenges such as transportation difficulties, safety concerns, pandemic restrictions, inflexible work schedules, or physical limitations hinder traditional mental health services. A straightforward policy measure to enhance access is to increase public awareness of these

services, ensuring that those most in need are informed about their availability.

Summary and primary audience: In summary, on the practical side, the primary audience of our study are (1) platform designers and product teams who can use our actionable guidance (discussed in the next section on future research opportunities) to reduce feature-induced discomfort; (2) healthcare decision-makers and procurement leads who can use appropriate criteria for selecting and configuring means of communication (e.g., online platforms) and for onboarding that addresses disclosure-critical factors (e.g., by cultivating a positive and accepting environment); (3) mental health professionals who can learn from our findings and adopt session practices that mitigate perceived social risk during intake (e.g., by increasing privacy or actively promoting approach-focused goals); and (4) policy makers who can advocate the expansion of telemental health services especially for those without access to traditional in-person services. Given the scope of our study and the provided evidence, it is essential to note that all the above-mentioned implications apply to early sessions of non-emergency telemental health; any broader generalizations should be pursued with caution, as they will fall outside the present study's boundary conditions.

Limitations and Future Research Opportunities

This study makes important contributions to information self-disclosure, stigma, and IT healthcare research; however, it is essential to acknowledge its limitations, which simultaneously pave the way for future research. First, the online nature of data collection introduces potential sampling bias. Participants were recruited through Prolific Academic, indicating a level of digital literacy not universally shared. This raises concerns about the representativeness of our sample, as those who could benefit most from telemedicine might need greater digital acumen. Future research should therefore investigate strategies to engage and study populations with lower digital literacy (e.g., non-digital natives), thereby enriching understanding of this group's needs and barriers. This could involve developing and testing a simplified telehealth platform with intuitive interfaces and minimal text, potentially using visual or audio aids to facilitate more straightforward navigation and use. The project would evaluate how these design changes impact information disclosure and the overall effectiveness of telehealth services in communities with varying levels of digital literacy. Lower-income individuals are another vital group that is not particularly targeted

in our study and merit further scrutiny in future studies.

Second, our theoretical foundations are based on the novel TIDM, drawing from the DPM [19] and existing literature on stigma and help-seeking behaviors, encompassing both personal and perceived public stigma [68]. Future research could adopt alternative stigma frameworks to critically examine how different types of stigma—personal or perceived public stigma—may alter the dynamics observed in this study. This approach could provide a more nuanced understanding of the stigma-related factors influencing information disclosure in telehealth contexts. For example, this could involve a longitudinal approach, surveying patients to observe changes in their perceptions of stigma and how these changes correlate with their willingness to use telehealth platforms for mental health disclosure. The study would provide insights into how stigma influences telehealth utilization and the effectiveness of interventions to reduce stigma.

Third, the TIDM primarily examines a limited set of factors influencing information disclosure. Subsequent studies should expand this scope by exploring additional influential factors and integrating novel mediators and moderators from emerging theories. The focus was on trust in technology, social presence, and information richness of the communication medium, along with controls for disposition towards trust, distrust, and general privacy concerns. However, further research is needed to examine the effects of technological affordances and design-related aspects on stigma and self-disclosure. Findings suggest that social presence and information richness, as broad characteristics of the communication medium derived from the TAM literature, can guide future research into specific technological features that vary along these dimensions. Future research could adopt social presence and information richness as foundational, high-level characteristics of communication media. Building on this baseline, studies can manipulate specific design variations that rank higher or lower on either of these dimensions and examine their broader impacts across relevant domains. For example, the presence or absence of nonverbal cues (e.g., the interlocutor's facial expressions) can increase or decrease social presence. For instance, text-based, voice-based, and video-based interactions are expected to have increasing levels of social presence in that order.

Anonymity perceptions and anonymized peer support features, in particular, merit closer examination

due to their complex, multidimensional nature and significant impact on IT design and use [94, 97]. For example, it has been shown that self-view features and seeing oneself on camera can lead to self-consciousness and reduced authenticity and openness [10, 23]; this, in turn, can result in decreased self-disclosure. Therefore, turning the camera off or using a voice-based platform might incentivize clients to increase their disclosure volume and authenticity. Other promising directions for future studies could include the introduction of AI-driven conversational agents (in text-based, voice-based, and video- or avatar-based formats), altering perceptions of social presence and information richness through anthropomorphization, and enhancing conversational and empathetic expression capabilities [18, 86, 110]. Moreover, this study used intentions to disclose information as a proxy for actual disclosure behavior among mental health patients. Finally, more research is needed on the emerging problem of people using GenAI for self-disclosure and self-help for mental health issues, when many users may over-rely on GenAI's advice and answers, which are often incorrect [cf. 87] and where hyper-personalization may introduce bias [cf. 137], which is particularly dangerous for mental health care.

Overreliance on self-reported measures is a key limitation of this study, as these measures may not always reflect actual behavior; therefore, using more objective measures of information disclosure could yield greater insights. Although direct data collection from mental health patients is ideal, legal barriers, such as HIPAA regulations and IRB considerations, make this challenging. Nonetheless, future research might explore anonymized hypothetical scenarios with actual mental health patients or conduct anonymized longitudinal studies that gather retrospective accounts of mental health service use. Among other potentially practical approaches are consented field studies linking session transcripts and EHR intake notes to coded disclosure events; telemetry or chat logs capturing actual self-disclosures (with differential privacy); incentive-compatible tasks revealing sensitive info for real stakes; micro-randomized or A/B tests varying feature cues and observing revealed content; and lab observations with staged clinical intakes coded by blinded raters. Another promising option would be using archival and observational data, analyzing real-world digital trace data, and extending to the study of chatbots for mental health [e.g., 9, 115], studying alternative mental healthcare delivery through AR/VR or metaverse settings where haptics-related data

could be gathered [e.g., 92], studying human-AI collaboration [e.g., 87], or recording chatlogs (in studies that use chatbots and conversational AI agents) for more reliable results. These approaches could yield more direct and objective insights into patients' mental health disclosure behaviors and experiences.

Finally, our comparison between face-to-face and remote therapy sessions, although limited in its reach regarding online platform design, can serve as a baseline for more granular examinations by future scholars. More specifically, for healthcare providers and IT developers, the findings stress the importance of designing telehealth platforms emphasizing trust, privacy, and ease of disclosure. A vital element of this is reducing the stigma associated with specific mental health conditions, which requires an environment that is safe and supportive and carefully monitored to prevent bullying and stigmatizing comments. Our study focused on the baseline for remote versus in-person telehealth settings. It used SPIR as a high-level characteristic of the communication medium (i.e., perceived social presence and information richness cues, measured constructs rather than manipulated features) that can be applied to more nuanced instances of IT artifacts and online platforms in practice. For example, given that telehealth platforms vary in SPIR, platform designers and system developers can test user interface designs high in social presence, information richness, or both, thereby maximizing patient engagement and information self-disclosure in the mental health context. Among the ways of testing such approaches are factorial and within-subject vignette experiments isolating avatar-based therapy, chatbot co-pilots, recording indicators, gaze-alignment, nonverbal feedback cues, background blur, anonymity controls, and consent messaging; mechanism tests with SPIR mediation and stigma or disclosure-goal moderation; and complementary field A/B tests and micro-randomized trials in live telehealth platforms with preregistration and transparency. These can yield highly insightful and practical findings, leading to better patient engagement and improved clinical outcomes.

Conclusion

Our study tackles the escalating global mental health crisis—a situation exacerbated by the COVID-19 pandemic that has sharply increased the incidence of mental health disorders and their accompanying economic and societal burdens. Beyond financial strain, the psychological and emotional impacts on

individuals, families, and communities are profound, manifesting in outcomes such as cognitive decline and, in severe cases, fatalities. In this challenging context, telehealth has emerged as a critical tool, and its importance was underscored during the pandemic. Notably, the VSee telehealth platform demonstrates the vital role of patient information disclosure in effective mental health care. Central to our research is the examination of the DPM within a stigmatized telehealth environment, where we explore how trust in technology and the SPIR of telehealth platforms influence patients' willingness to disclose sensitive information—a factor particularly crucial given that stigma often deters individuals from seeking treatment.

Our findings carry significant theoretical and practical implications. They reveal that specific high-level characteristics of the communication medium (e.g., in-person or remote mode of interaction) can facilitate the disclosure of stigmatized information, thereby enhancing the overall effectiveness of mental health care. As mental health needs continue to rise, our research underscores the necessity of developing telehealth solutions that are sensitive to the nuances of patient trust and stigma. These insights offer valuable guidance for scholars and practitioners, charting a course toward more accessible and effective mental healthcare services in a rapidly evolving landscape.

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Endnotes

[1] WHO (2025). "Over a billion people living with mental health conditions – services require urgent scale-up," World Health Organization (published September 2, 2025; last accessed February 20, 2026).

[2] The Carter Center (2018). "Mental Illness Will Cost the World $16 USD Trillion by 2030," Psychiatric Times Vol. 35 (11) (published November 16, 2018; updated November 16, 2020; last accessed February 20, 2026).

[3] In this study, when we refer broadly to "stigma," we denote societal-level devaluation of mental illness. When we refer to "perceived stigma," we specifically capture participants' expectations of negative social evaluation in the context of disclosure and treatment seeking in online or in-person mental healthcare settings. Importantly, there are several stigma-related constructs we formally distinguish as follows: (1) ***Public stigma***: Following Link and Phelan [88] and Corrigan [33], stigma refers to a social process in which labeling, stereotyping, separation, status loss, and discrimination co-occur within a context of power. In mental health, stigma manifests as negative societal beliefs (e.g., dangerousness, incompetence), prejudicial attitudes, and discriminatory behaviors directed toward individuals with mental illness [33, 111]. This definition captures stigma as a structural and interpersonal social phenomenon. (2) ***ADHD/Schizophrenia-related stigma***: ADHD/Schizophrenia-related stigma, which is the moderating variable in our proposed theoretical model, refers to disease-specific stigma which in our study is ADHD/Schizophrenia-related stigma [68] and points to the general perception or expectation about the level of stigma associated with a specific disease or disorder like schizophrenia or ADHD [68] In other words, disease-specific stigma, which plays a key role in our proposed model (see Figure 3 in the manuscript), is defined as the extent to which stigma and negative connotations are associated with ADHD and schizophrenia (the two disorders mentioned in our study).Within disclosure frameworks, such as the disclosure processes model [19], ADHD/schizophrenia-related stigma shapes disclosure goals and risk assessments by influencing expectations about negative social consequences. (3) ***Self-stigma (internalized stigma):*** Self-stigma occurs when people internalize public stigma and apply negative societal stereotypes to themselves, resulting in diminished self-esteem, reduced self-efficacy, and shame [34, 79]. Unlike perceived stigma, which concerns expectations about others' attitudes, self-stigma reflects internal cognitive–affective processes in which stigmatizing beliefs become self-defining. (4) ***Treatment stigma (help-seeking stigma)***: Treatment stigma refers specifically to stigma associated with seeking or receiving mental health services. It encompasses fears of being labeled, judged, or socially penalized for engaging in psychological treatment [26, 33]. Treatment stigma can operate even when people do not strongly endorse stereotypes about mental illness itself, thereby constituting a distinct barrier to care.

[4] NCMW (2025). "A Workforce Under Pressure: Preparing the Behavioral Health Workforce for Today and Tomorrow," National Council for Mental Wellbeing (published September 25, 2025; updated December 19, 2025; last accessed February 20, 2026).

[5] Pilot Test 1 was conducted with 50 valid responses. Aside from testing the measure, we tested the proper functioning of the randomization routine to ensure a balanced distribution of the four treatments (i.e., remote [n = 26], face-to-face [n = 24], ADHD [n = 24], and schizophrenia [n = 26]). Both manipulations showed statistically significant effects in the theorized directions; therefore, the manipulations were deemed successful. In addition, after receiving the comment "The video didn't have sound" from one of the respondents, to avoid similar problems in future versions, a new phrase was included in the online instrument immediately before showing the video: "Please make sure your audio is on (to hear the conversation)." We also checked the reliability of all constructs. All the measures except for perceived ADHD/schizophrenia-related stigma showed excellent reliability (i.e., Cronbach's alphas > 0.7). We also continued our literature review in parallel. We identified several control variables that the next version of the instrument should include (e.g., disposition to distrust, general privacy concerns, public stigma, treatment stigma, and self-stigma) to address endogeneity concerns.

These choices resulted in a longer survey. Thus, to avoid survey fatigue, we used the results of our first pilot test's reliability analysis and trimmed every control variable (e.g., disposition to trust, PIIT, trust in doctors) to have three items and every primary construct included in our baseline model (e.g., approach-focused and avoidance-focused disclosure goals) to have four items with the highest possible Cronbach's alpha as an end goal; these numbers are considered the bare minimum required to enable high-quality confirmatory factor analysis and structural equation modeling. Because we deemed it unnecessary, we eliminated the single-item question, "Imagine you were the patient in this scenario. How likely would you be to schedule a follow-up appointment with a

counselor?" which was intended to prime the subjects before they answered the SPIR-related questions; we consequently eliminated treatment 2 (remote vs. face-to-face).

Because the stigma construct is one of our conceptual model's focal concepts, a few changes were made to improve its suboptimal reliability (0.575). The first involved changing the wording of item 1, which seemed unnecessarily indirect, from the original "Please indicate how stigmatized you think ADHD/schizophrenia is" to "To what extent do you think stigma is associated with ADHD/schizophrenia?" The second change concerned the scale for item 1; we changed the scale's original wording, "Not stigmatized at all = 1 – Extremely stigmatized = 7," to "To an extremely small extent = 1 – To an extremely large extent = 7." The third change involved the wording of item 3, which seemed slightly confusing. The original item, "I would have felt ashamed if I had ADHD/schizophrenia," was changed to "I would feel ashamed if I had ADHD/schizophrenia." The final change concerned the location of the items. In Pilot Test 1, there were five questions between item 1 of the perceived ADHD/schizophrenia-related stigma construct and items 2 and 3. This design flaw was addressed by grouping all three items in the next iteration of the instrument. Based on the new constructs derived from prior literature—To address reliability issues, design problems, and concerns about survey fatigue, we conducted another pilot test (Pilot Test 2).

[6] In Pilot Test 2, we included all the new measures and the refined and trimmed versions of the old ones. In this test, all the constructs, including both perceived ADHD/schizophrenia-related stigma measures, showed excellent reliability (i.e., Cronbach's alphas > 0.7). Following the same logic as in Pilot Test 1, we used the reliability analysis results from our second pilot test to avoid survey fatigue in future versions. We trimmed every control variable (e.g., public stigma, self-stigma) to arrive at three reflective items with higher construct validity and reliability. We also checked the stigma manipulation (i.e., ADHD vs. schizophrenia) in Pilot Test 2. The results showed statistically significant differences for both the original and the refined perceived ADHD/schizophrenia-related stigma measure, but, unlike Pilot Test 1, nonsignificant differences for the SPIR construct (i.e., remote vs. face-to-face treatment). The one meaningful change made in Pilot Test 2 (as compared to Pilot Test 1) that could have caused this failure was asking the SPIR questions after the original perceived ADHD/schizophrenia-related stigma questions, thus increasing the distance between the videos (where both treatments were introduced) and the SPIR items by nine additional questions.

[7] In Pilot Test 3, with 52 valid responses, we trimmed every measure, except the primary constructs used in the baseline conceptual model (i.e., SPIR and antecedent disclosure goals), down to three items, again based on choosing the reflective items that maximized construct validity and reliability. All measures, except trust in doctors ($\alpha = 0.640$), showed excellent reliability (Cronbach's alphas > 0.7), and the survey, despite including all primary and control variables, took an average of 14 minutes to complete, thereby alleviating concerns about survey fatigue. We presented the SPIR questions immediately after the original perceived ADHD/schizophrenia-related stigma items (like Pilot Test 1). The manipulations worked properly and adequately, indicating a statistically significant difference for both stigma measures. Still, they failed to succeed in the SPIR measure (i.e., the remote vs. face-to-face construct).

In the final version of the instrument and before collecting the final dataset, two changes were made to address this problem. First, all four reverse-coded SPIR items were modified for a positive sign interpretation. Second, the priming single-item question (see Pilot Test 1 explanations for more details) was added to mimic the potentially valuable characteristics of Pilot Test 1, which was the only successful version with a statistically significant remote versus face-to-face SPIR difference. This treatment eventually showed statistically significant differences in the final dataset (as did the other treatment, i.e., ADHD vs. schizophrenia), rendering all three pilot studies very helpful in achieving a lean, high-quality, and fully functioning online instrument.

[8] The video manipulations are embedded in the links as follows:

- ADHD (Remote/Virtual)
- Schizophrenia (Remote/Virtual)
- ADHD (Face-to-Face/In-Person)
- Schizophrenia (Face-to-Face/In-Person)

[9] "The Health Insurance Portability and Accountability Act of 1996 (HIPAA) is a federal [US] law that required the creation of national standards to protect sensitive patient health information from being disclosed without the patient's consent or knowledge" (CDC, 2019, p. 1).

Appendix A: Measures Used in This Research

Construct (Source)	Prompts and Items	Acronym/ Manipulation check
Antecedent disclosure goals, Chaudoir and Fisher [5]	**Prompt**: Please indicate whether you agree or disagree with the following statements: (The assumption for these questions is that you are either a university student or a working professional)	n/a
	It is important for me to do better than other students/coworkers in my university classes/at work.	Goal1.1
	My goal in my university classes / at work is to get a better *grade/rating* than most of the other students/coworkers.	Goal1.2
	I am motivated by the thought of outperforming my peers in my university classes / at work.	Goal1.3
	It is important for me to do well compared to others in my university classes / at work.	Goal1.4
	I often think to myself, "What if I do badly in my university classes / at work?"	Goal2.1
	I worry about the possibility of getting bad grades/ratings in my university classes / at work.	Goal2.2
	My fear of performing poorly in my university *classes/at work* is often what motivates me.	Goal2.3
	I just want to avoid doing poorly in my university *classes/at work*.	Goal2.4
Disposition to trust, Gefen [11]	Most people are honest in describing their experience and abilities.	DispT1
	Most people can be counted on to do what they say they will do.	DispT2
	Most people are competent in terms of their work.	DispT3
Disposition to distrust, Everard and Galletta [9]	People pretend to care more about one another than they really do.	DispD1
	Most people would tell a lie if they could gain by it.	DispD2
	Most people would cheat on their income tax if they thought they could get away with it.	DispD3
General privacy concerns, Culnan [6]	I am concerned about threats to my personal privacy.	GPrv1
	I think my personal privacy is threatened.	GPrv2
	Threats to my personal privacy concern me.	GPrv3
PIIT, Culnan [6]	If I heard about a new information technology, I would look for ways to experiment with it.	PIIT1
	Among my peers, I am usually the first to try out new information technologies.	PIIT2
	I like to experiment with new information technologies.	PIIT3
Public stigma, Kanter et al. [14]	Other people with mental health disorders are not worth the time and resources.	StigP1
	Everyone can plainly see that other people with mental health disorders are inferior.	StigP2
	Other people with mental health disorders are morally weak.	StigP3
Treatment stigma, Kanter et al. [14]	Receiving treatment for mental health disorders carries social stigma.	StigT1
	People will see a person in a less favorable way, if they come to know that he/she has received treatment for a mental health disorder.	StigT2
	People tend to like less those who are receiving professional help for a mental health disorder.	StigT3
Self-stigma, Kanter et al. [14]	Others would view me as weak if I had a mental health disorder.	StigS1
	If people learned that I had a mental health disorder, they would look for flaws in my character.	StigS2
	If some people knew I had a mental health disorder they would grow more distant.	StigS3
ADHD/Schizophrenia-related stigma, Hatzenbuehler et al.	**Prompt**: Please indicate whether you agree or disagree with the following statements: (1–7: Strongly disagree–strongly agree)	**Manipulation Check**
	To what extent do you think that stigma is associated with ADHD/Schizophrenia?	StigAS1

[13]	Most people are afraid to be around people with ADHD/Schizophrenia.	StigAS2
	I would feel ashamed if I had ADHD/Schizophrenia.	StigAS3
SPIR, Straub [23]	**Prompt**: Please indicate the degree to which you believe the interaction between the patient and the therapist in this *remote/fact-to-face* therapy session can be categorized as stated in the following statements.	**Manipulation Check**
	The remote/face-to-face therapy session was (1–7: Extremely impersonal–extremely personal)	SPIR1
	The therapist was (1–7: Extremely unsociable–extremely sociable)	SPIR2
	The remote/face-to-face therapy session was (1–7: Extremely cold–extremely warm)	SPIR3
	The therapist was (1–7: Extremely insensitive–extremely sensitive)	SPIR4
Trust in the doctor, Anderson and Dedrick [2]	**Prompt**: For the following questions, imagine you were the patient in this scenario (shown in the video).	n/a
	My doctor is usually considerate of my needs and puts them first.	TrstDt1
	I trust my doctor so much I always try to follow his/her advice.	TrstDt2
	I feel my doctor does not do everything he/she should about my mental health care.	TrstDt3*
Trust in technology, (TT) McKnight et al. [20]	**Prompt**: Only for the virtual treatment. For the following questions, imagine you were the patient in this scenario (shown in the video). Please indicate whether you agree or disagree with the following statements.	n/a
	The VSee videoconferencing platform has enough safeguards to make me feel comfortable using it for a virtual therapy session.	TT1
	I feel assured that legal and technological structures adequately protect me from problems on the VSee videoconferencing platform when using it for a virtual therapy session.	TT2
	I feel confident that encryption and other technological advances on the VSee videoconferencing platform make it safe for me to transact there for a virtual therapy session.	TT3
Intention to disclose, (ITD) Anderson and Agarwal [1]	**Prompt**: For the next three questions, imagine you were the patient in the video.	n/a
	How likely would you be to share your private/personal information with the therapist? (1–7: Extremely unlikely–extremely likely)	Disc1
	How comfortable would you be to share your private/personal information with the therapist? (1–7: Extremely uncomfortable–extremely comfortable)	Disc2
	How willing would you be to share your private/personal information with the therapist? (1–7: Extremely willing–extremely unwilling)	Disc3*
Direct experience with mental health concerns	Have you ever suffered (or are currently suffering) from metal health problems? (Yes/No/Prefer not to answer)	Exp1
Indirect experience with mental health concerns	Has any of your loved ones ever suffered (or are currently suffering) from metal health problems? (Yes/No/Prefer not to answer)	Exp2
Social desirability, Anderson and Agarwal [1]	**Prompt**: Please indicate whether you agree or disagree with the following statements:	n/a
	I never lie.	SoDes1
	I never get angry.	SoDes2
	I tell the truth every single time.	SoDes3

Note: Items with * in front of their acronyms were reverse-coded items. All measures are reflective. PIIT = personal innovativeness with IT; SPIR = social presence and information richness; TT = trust in technology.

Appendix B: Analysis Support

Appendix B.1. Descriptive Statistics, Reliabilities, Validities, and Correlations

Table B.1. Descriptive Statistics, Reliabilities, Validities, and Correlations

Variables	Mean	SD	CA	CR	AVE	VIF	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 Intention to disclose	5.25	1.46	0.93	0.94	0.85	—	**0.920**																				
2 Antecedent goals	0.00	1.75	0.87	0.86	0.51	1.14	−0.07	**0.717**																			
3 Antecedent goal 1	4.56	1.57	0.95	0.95	0.81	1.32	−0.02	0.63	**0.902**																		
4 Antecedent goal 2	4.55	1.43	0.87	0.88	0.64	1.24	0.06	−0.53	0.32	**0.802**																	
5 Trust in technology	4.96	1.43	0.97	0.97	0.91	1.33	0.55	−0.06	0.07	0.15	**0.952**																
6 Stigma (ADHD/Schiz.)	3.97	1.01	0.82	0.83	0.63	1.11	−0.17	−0.04	0.08	0.14	−0.11	**0.792**															
7 SPIR	5.12	1.11	0.88	0.89	0.67	1.36	0.31	−0.01	0.05	0.07	0.25	0.13	**0.816**														
8 Public stigma	1.67	0.95	0.88	0.89	0.73	1.13	−0.16	0.11	0.04	−0.09	−0.09	0.13	−0.04	**0.853**													
9 Treatment stigma	4.64	1.13	0.85	0.86	0.68	1.96	0.01	−0.02	0.06	0.09	−0.06	0.15	0.04	0.11	**0.822**												
10 Self-stigma	4.50	1.32	0.88	0.89	0.72	2.08	−0.01	−0.06	0.08	0.16	−0.04	0.20	0.13	0.18	0.69	**0.850**											
11 Trust in doctor	4.90	1.14	0.75	0.79	0.58	1.41	0.42	−0.01	0.04	0.06	0.42	−0.08	0.41	−0.11	−0.04	0.00	**0.761**										
12 Disposition to trust	4.86	0.99	0.84	0.84	0.64	1.51	0.25	0.11	0.03	−0.09	0.18	−0.01	0.27	−0.23	−0.10	−0.08	0.23	**0.801**									
13 Disposition to distrust	4.51	1.25	0.80	0.81	0.60	1.37	−0.10	0.01	0.17	0.17	0.03	−0.10	−0.06	0.18	0.19	0.22	−0.07	−0.46	**0.772**								
14 Privacy concerns	4.77	1.41	0.92	0.92	0.80	1.09	−0.02	0.05	0.01	−0.05	−0.16	−0.01	0.08	0.05	0.12	0.10	−0.01	−0.13	0.12	**0.892**							
15 PIIT	4.60	1.51	0.92	0.92	0.79	1.11	0.08	0.26	0.35	0.08	0.11	0.09	0.03	0.01	0.06	0.07	0.05	0.07	0.00	−0.02	**0.890**						
16 Direct experience	1.52	0.64	—	—	—	—	−0.05	0.19	0.01	−0.22	0.01	0.10	0.05	0.27	−0.10	−0.03	0.04	0.11	−0.11	0.02	0.09	—					
17 Indirect experience	1.37	0.61	—	—	—	—	−0.07	0.12	−0.05	−0.20	0.04	0.09	0.00	0.23	−0.07	−0.02	0.11	0.06	−0.06	0.04	−0.03	0.47	—				
18 Age	46.03	16.09	—	—	—	—	0.04	0.19	−0.02	−0.26	−0.06	0.04	0.00	0.00	−0.10	0.02	−0.03	0.09	−0.16	0.10	−0.07	0.19	0.11	—			
19 Female	0.53	0.50	—	—	—	—	0.01	−0.11	−0.05	0.07	0.03	−0.05	−0.04	−0.19	−0.12	−0.10	0.01	0.06	−0.08	−0.08	−0.14	−0.22	−0.20	0.01	—		
20 Income	3.04	1.63	—	—	—	—	0.08	0.13	0.18	0.04	0.07	0.04	0.01	−0.03	0.00	−0.05	0.09	0.04	0.01	−0.01	0.14	0.04	−0.07	−0.11	−0.01	—	
21 Race	1.55	1.34	—	—	—	—	−0.06	−0.07	−0.07	0.01	−0.02	0.18	0.04	0.09	0.12	0.12	−0.13	−0.03	0.00	−0.01	0.05	−0.02	0.02	−0.08	−0.01	0.01	—
22 Education	3.41	1.17	—	—	—	—	0.11	0.19	0.16	−0.06	0.10	0.02	−0.10	−0.06	−0.04	−0.03	0.12	0.02	0.02	0.06	0.08	0.10	0.02	0.16	0.05	0.37	−0.07

Note: n = 309; SD: standard deviation; CA: Cronbach's alpha; CR: composite reliability; AVE: average variance extracted. VIF: variance inflation factor. The bolded numbers down the diagonal are the square roots of AVEs. Antecedent goals 1 correspond to approach-focused disclosure goals, whereas antecedent goals 2 correspond to avoidance-focused disclosure goals; hence, they are treated as two separate measures. See the "Measures" section in the manuscript for more details on how these two measures were aggregated into a single variable (i.e., the antecedent goals) for hypothesis testing purposes in this study. The AVE for the aggregated antecedent goals measure was lower than 0.50 (i.e., 0.457); therefore, the item with the lowest factor loading and highest cross-loading (i.e., Gola2.4) was dropped from the aggregated measure, increasing the AVE to an acceptable level: 0.514. PIIT = personal innovativeness with IT; SPIR = social presence and information richness.

Appendix B.2. Factor Loadings and Cross Loadings

Table B.2. Factor Loadings and Cross Loadings

Items	ITD	Goal1	Goal2	TT	StigAS	SPIR	StigP	StigT	StigS	TrstDt	DispT	DispD	GPrv	PIIT
ITD1	.844	.004	.002	.130	-.016	-.028	-.075	.023	-.002	-.008	-.009	.017	-.002	.015
ITD2	.977	-.001	-.019	-.072	-.002	.001	.070	.006	-.009	.004	.002	.003	-.006	-.023
ITD3	.919	.003	.005	.062	-.022	-.013	-.013	-.012	-.006	-.002	.003	.039	.026	-.001
Goal1.1	.006	-.948	-.030	-.054	-.014	-.020	-.005	.031	-.006	.026	.027	-.057	-.011	.020
Goal1.2	.022	-.915	.005	.042	.033	.022	.018	-.021	.062	-.007	-.076	.024	.002	-.018
Goal1.3	.009	-.901	-.049	.047	-.004	.004	.056	-.022	-.025	-.027	.003	-.009	.048	-.039
Goal1.4	-.039	-.879	-.014	-.048	-.002	-.010	-.058	.049	-.085	.019	.039	-.013	-.060	-.049
Goal2.1	.026	.022	-.901	.025	-.010	.034	.023	.047	-.017	-.049	.095	-.027	.024	.000
Goal2.2	-.006	-.067	-.884	.052	-.029	.037	-.042	-.031	.044	-.054	.009	.069	-.029	.038
Goal2.3	-.037	-.157	-.814	.023	.021	-.051	-.008	-.032	-.020	-.020	-.060	.010	.054	.034
Goal2.4	.027	.070	-.739	-.069	.051	-.019	-.011	.011	.028	.132	-.071	-.053	-.059	-.065
TT1	.029	.039	.001	.949	.030	.002	-.006	.021	-.027	.022	-.013	.010	.024	-.015
TT2	.000	-.011	-.008	.952	-.019	-.004	.006	.007	-.014	.006	.040	-.023	-.032	-.006
TT3	.014	-.007	.000	.957	-.023	-.009	-.010	.035	-.021	.002	-.020	.007	-.038	-.008
StigAS1	.053	-.012	-.034	-.017	.882	.043	-.102	.184	-.067	-.030	.053	-.072	-.003	.021
StigAS2	-.004	-.009	.040	-.069	.881	-.097	.067	-.014	-.066	-.030	.058	-.015	-.013	-.045
StigAS3	-.146	-.004	-.056	.056	.737	-.002	.112	-.177	.205	.018	-.087	.095	.030	-.008
SPIR1	-.002	-.028	-.030	-.009	-.038	-.794	.003	-.059	.142	-.018	.051	.077	.077	-.002
SPIR2	.011	-.055	.059	.056	.031	-.889	.046	.030	-.035	-.040	-.004	.024	.044	.050
SPIR3	-.038	-.017	.004	.031	-.039	-.868	-.009	-.007	-.015	.045	.042	-.051	-.018	-.043
SPIR4	.076	.100	-.026	-.049	.083	-.846	-.064	.056	-.078	.065	-.050	-.025	-.090	-.002
StigP1	.052	.033	-.001	-.012	.027	.042	.908	-.016	-.029	.030	-.015	.009	.004	-.009
StigP2	.005	.025	-.038	.020	-.015	-.018	.910	.068	-.018	-.004	-.002	-.069	-.022	.018
StigP3	-.047	-.068	.072	-.021	.013	-.006	.882	-.038	.034	-.007	.019	.023	-.003	.003
StigT1	.027	.015	-.081	.032	.026	-.030	.023	.846	.044	-.049	.036	-.029	.074	.000
StigT2	-.023	-.068	.073	.015	.056	.009	-.013	.763	.254	.063	-.068	.003	.007	.008
StigT3	.017	-.030	.039	-.025	-.009	.010	.040	.586	.428	.062	-.018	-.018	-.047	-.039
StigS1	.034	-.026	-.076	-.006	-.009	-.064	.086	.201	.745	-.048	-.003	.039	.059	.043
StigS2	-.024	.026	-.039	-.019	.051	.006	-.067	.060	.866	-.014	.007	-.040	.007	-.011
StigS3	-.012	.030	.014	-.040	.007	-.007	.042	.091	.838	-.009	-.011	-.070	-.028	-.047
TrstDt1	.149	-.064	-.017	.080	-.016	-.103	.005	-.111	.096	.727	.060	-.060	.021	.006
TrstDt2	.171	-.026	-.025	.180	.002	-.089	-.035	-.227	.179	.597	.101	-.124	-.028	-.009
TrstDt3	-.084	.028	.002	-.017	-.032	.005	.014	.132	-.137	.854	-.022	.097	.027	.007
DispT1	.035	-.034	.025	.007	.040	-.042	-.025	-.091	.052	-.020	.776	.116	-.046	-.026
DispT2	.022	-.093	.052	-.006	.056	.016	.008	.023	-.004	.039	.848	.071	.020	.003
DispT3	-.035	.098	-.044	.016	-.037	-.014	.003	.045	-.026	.004	.890	-.054	-.006	.003
DispD1	-.057	.004	-.078	.038	-.067	-.048	.145	.012	.049	-.106	-.087	-.691	.028	-.036
DispD2	-.035	.019	-.045	-.014	.013	.007	.011	.065	-.096	-.012	-.050	-.868	.003	-.009
DispD3	.022	-.081	.082	-.001	.050	.049	-.060	-.065	.095	.051	.000	-.866	.020	.047
GPrv1	-.005	.004	-.025	-.023	.006	.000	-.029	-.040	.030	.010	-.004	-.029	.951	.000
GPrv2	.034	.005	.066	-.027	.000	.009	.017	.047	-.014	.009	-.078	-.019	.889	.001
GPrv3	-.011	.017	-.023	.009	.001	-.013	-.012	.015	-.028	.016	.061	.015	.927	-.017
PIIT1	.017	-.017	-.001	-.013	-.010	.018	-.033	-.037	.048	.004	.065	.002	.013	-.919
PIIT2	.058	-.007	.015	.003	.032	.045	.045	.019	-.017	.014	-.034	.050	-.011	-.903
PIIT3	-.066	-.024	-.009	.034	-.017	-.057	-.026	.019	-.029	-.032	-.021	-.039	.016	-.940

Note: All factor loadings are above 0.50 and average above 0.70 for each construct. Loadings of 0.400 or lower are visually suppressed in each table interpretation. Factor loading of each item is higher on its corresponding construct than on others. Please note that items Goal1.1–Goal1.4 correspond to approach-focused disclosure goals, while items Goal2.1–Goal2.4 correspond to avoidance-focused disclosure goals; hence, their loadings fall on two separate dimensions. See the "Measures" section in the manuscript for more details on how the disclosure goals construct was aggregated into a single variable for hypothesis testing purposes in this study.

DispD = disposition to distrust; DispT = disposition to trust; Goal1 = approach-focused disclosure goals; Goal2 = avoidance-focused disclosure goals; GPrv = general privacy concern; ITD = intention to disclose; PIIT = personal innovativeness in information technology; StigAS = ADHD/Schizophrenia-related stigma; SPIR = social presence information richness; StigP = public stigma; StigT = treatment stigma; StigS = Self-Stigma; TrstDt = trust in doctor; TT = trust in technology.

Appendix B.3. Non-Response Bias Results and Explanations

Table B.3. Non-Response Bias Results

Variable	*t*-value	*p*-value
Antecedent goals	-0.58	0.70
Approach-focused goals	-0.13	0.90
Avoidance-focused goals	0.70	0.36
Public stigma	-0.42	0.81
Treatment stigma	-0.84	0.70
Self-stigma	-2.10	0.45
Trust in doctors	-0.96	0.05
Disposition to trust	-1.75	0.67
Disposition to distrust	1.48	0.51
General privacy concerns	-1.64	0.49
PIIT	-1.50	0.76
Direct experience	-1.52	0.83
Indirect experience	-1.61	0.20
Age	-6.47	0.07
Gender	2.85	<0.01
Income	-0.73	0.45
Race	0.41	0.27
Education	-1.27	0.08
n	62	62

Note: The results indicate independent samples *t*-test results for the 1st and the last 10%; PIIT = personal innovativeness with IT.

Testing for nonresponse bias involved comparing the first 10% (early wave) and the last 10% (late wave) of responses to check for nonresponse bias [3]. This categorization into 31 early and 31 late responses enabled a t-test comparison of crucial variables between the groups. As shown in the randomization checks results in the manuscript (i.e., Table 2), there were no significant differences in various measures, including antecedent, approach-focused, and avoidance-focused goals and perceptions of stigma and trust. This lack of significant variance affirms that nonresponse bias is not a concern in our study.

Appendix B.4. Common Method Bias and Social Desirability Bias Test Results

Before data collection, we addressed the potential for common-method bias (CMB) inherent in single-source data collection [19, 21]. First, the survey instrument was refined through pilot testing to optimize length, design, and engagement, evidenced by the low response failure rate and high data quality. Second, procedural controls were included to increase respondent anonymity, emphasizing response accuracy and incorporating multiple attention check questions [17, 19, 22]. We also designed our study to reduce social desirability bias, which can also minimize CMB [19, 22].

After data collection, we also conducted a one-factor test, revealing that a single factor accounted for only 13.26% of the variance, well below the 50% threshold associated with CMB concerns [10, 16]. Exploring interaction effects further mitigated CMB risk [7]. Furthermore, correlations between latent variables did not exceed 0.70, well below the 0.90 threshold for significant shared variance concerns [18], as detailed in **Table B.1**.

Finally, we collected data on social desirability as a latent factor to address potential social desirability bias in this highly stigmatized context. We used a chi-square difference test to compare models with and without this bias. The significant difference between the two models indicated the presence of social desirability bias (see **Table B.4)**. To mitigate this bias, we retained the specific bias factor for factor score imputation, allowing for bias-adjusted causal modeling [19, 22, 24]. This latent variable did not disrupt the model, as all items remained significant predictors of their respective constructs, providing further evidence of the absence of CMB and social desirability bias. The constructs displayed excellent reliability and

validity; the overall model maintained an excellent fit.

Table B.4. Social Desirability Bias Test Results

Unconstrained	1708.898	913	< 0.001
Fully Constrained	1794.799	957	< 0.001
Difference	85.901	44	< 0.001

Note: The results indicate that the models differ significantly.

Appendix B.5. Robustness Check 1: Results for Social Desirability Bias-Adjusted Measures

Table B.5. Robustness Check 1: Results for Social Desirability Bias-Adjusted Measures

Variable	TT	*p*-value	ITD	*p*-value
Antecedent goals	-0.21***	<0.001	-0.06	0.205
Trust in technology	—	—	0.37***	<0.001
Goals → TT → Disc	—	—	-0.10**	0.001
StigmaAS	-0.25***	<0.001	-0.18***	<0.001
Goals × StigmaAS	-0.10*	0.025	—	—
SPIR	0.07	0.241	0.13**	0.019
Public stigma	0.07	0.192	-0.02	0.667
Treatment stigma	0.11	0.191	0.13	0.101
Self-stigma	-0.18*	0.039	-0.08	0.374
Trust in doctors	0.44***	<0.001	0.37***	<0.001
Disposition to trust	0.21***	<0.001	0.02*	0.018
Disposition to distrust	0.22*	<0.001	-0.13	0.248
General privacy concerns	-0.17***	<0.001	0.06	0.154
PIIT	0.14**	0.002	0.03	0.465
Direct experience	-0.01	0.796	-0.07	0.190
Indirect experience	0.02	0.736	-0.07	0.159
Social desirability	0.07†	0.099	-0.07	0.103
Age	0.02	0.632	0.09*	0.042
Female	0.04	0.437	-0.01	0.882
Income: < $25K	-0.08	0.104	0.06	0.235
$50K–$74.9K	-0.15**	0.004	0.01	0.779
$75K–$99.9K	-0.01	0.773	0.00	0.983
$100K–$149.9K	-0.08†	0.097	-0.05	0.289
$150K–$200K	0.00	0.945	-0.06	0.096
> $200K	-0.04	0.401	0.07	0.188
Race: Black	0.06	0.163	-0.03	0.569
Asian	0.04	0.334	-0.02	0.620
Other	0.02	0.595	0.00	0.964
Education: < HS	-0.03	0.514	-0.07†	0.090
High school diploma	-0.02	0.642	-0.08	0.131
Associate degree	0.01	0.791	-0.02	0.685
Master's degree	0.03	0.493	-0.08†	0.067
Doctoral degree	0.06	0.189	0.04	0.342
R^2	0.46	—	0.51	—

Note: n = 309. *** significant at 0.001; ** significant at 0.01; * significant at 0.05; †significant at 0.10. The standardized estimates are reported in the table. Goals → TT → Disc represents the mediation effect (i.e., the indirect effect of antecedent goals on intention to disclose through trust in technology). For gender, male was the benchmark; for race, white was the benchmark; for income, the category $25K−$49.9K was the benchmark; and for education, a bachelor's degree was the benchmark. ITD = intention to disclose; PIIT = personal innovativeness with IT; SPIR = social presence and information richness; TT = trust in technology.

Appendix B.6. Robustness Check 2: Results for Hayes Process Model

Table B.6. Robustness Check 2: Results for Hayes Process Model 8

Variable	TT	*p*-value	ITD	*p*-value
Antecedent goals	-0.13**	0.008	-0.07	0.131
Trust in technology	—	—	0.43***	<0.001
Goals → TT → Disc	—	—	-0.05*	—
StigmaAS	-0.19**	0.019	-0.22**	0.003
Goals × StigmaAS	-0.08†	0.052	—	—
SPIR	0.15†	0.061	0.18*	0.015
Public stigma	-0.01	0.954	-0.03	0.674
Treatment stigma	0.04	0.644	0.12	0.154
Self-stigma	0.09	0.247	-0.02	0.808
Trust in doctors	0.41***	<0.001	0.20**	0.006
Disposition to trust	0.19*	0.040	0.18*	0.027
Disposition to distrust	0.15*	0.031	-0.04	0.481
General privacy concerns	-0.19**	0.001	0.04	0.454
PIIT	0.11*	0.035	0.03	0.485
Direct experience	0.00	0.989	-0.11	0.398
Indirect experience	0.06	0.666	-0.17	0.198
Age	0.00	0.877	0.01†	0.050
Female	0.00	0.999	-0.09	0.507
Income: < $25K	-0.31	0.171	-0.08	0.701
$50K–$74.9K	-0.54*	0.019	0.16	0.442
$75K–$99.9K	0.03	0.894	0.15	0.496
$100K–$149.9K	-0.18	0.462	0.00	0.999
$150K–$200K	-0.09	0.817	-0.58	0.105
> $200K	-0.34	0.422	0.58	0.133
Race: Black	0.33	0.172	-0.09	0.690
Asian	0.15	0.642	-0.19	0.532
Other	0.00	0.997	-0.04	0.909
Education: < HS	-0.10	0.850	-0.69	0.168
High school diploma	-0.12	0.549	-0.22	0.225
Associate degree	-0.01	0.949	-0.08	0.709
Master's degree	0.19	0.419	-0.29	0.180
Doctoral degree	1.03†	0.050	0.70	0.140
R^2	0.30	—	0.45	—

Note: n = 309. *** significant at 0.001; ** significant at 0.01; * significant at 0.05; †significant at 0.10. The standardized estimates are reported in the table. Goals → TT → Disc represents the mediation effect (i.e., the indirect effect of antecedent goals on intention to disclose through trust in technology). For this indirect effect, as per the Hayes PROCESS procedures, a *p*-value was not calculated; the lower and upper bounds of the bootstrapped confidence interval were -0.1039 and -0.0115, respectively, indicating a significant relationship (because the interval does not include zero). For gender, male was the benchmark; for race, white was the benchmark; for income, the category $25K−$49.9K was the benchmark; and for education, a bachelor's degree was the benchmark. ITD = intention to disclose; PIIT = personal innovativeness with IT; SPIR = social presence and information richness; TT = trust in technology.

Appendix C: Mapping of Subject Perceptions to Group Assignments

Single-item measures usually do not work well for assessing complex constructs, and there is ample evidence warning researchers against using them, and overwhelming support for the use of multi-item constructs for multidimensional constructs [8, 12]. SPIR and stigma are complex, multifaceted constructs (as noted in prior literature, which identifies multiple facets and subdimensions of these constructs); thus, using a single-item measure would be both a theoretical and an empirical mistake. For instance, there is abundant evidence supporting using multi-item constructs for complex concepts like stigma [15, 25].

Generally, there are three major concerns regarding the use of single-item scales: firstly, they cannot capture the essence of the construct; in other words, they cannot adequately address the topic (i.e., they are deficient in content

validity) and this effect is amplified for more complex concepts, secondly, they entail considerably fewer points of discrimination (leading to substantially inferior sensitivity), and lastly, they lack any measure of internal consistency (i.e., the scale's reliability cannot be assessed) [8, 12]. Given the sensitivity of the topic and the significance of even small variations in clients' perceptions and reactions, we believe these aspects are of great importance in the mental health context.

Appendix D: Alternative Theories Considered

Before settling on the DPM, the regulatory focus theory (RFT) [4] was considered as a candidate reference theory. Although helpful for conceptualizing motivations and goals, RFT is quite broad in scope because it addresses goal pursuit in general, whereas the DPM focuses exclusively on one specific goal: information disclosure in a stigmatized context. In short, the DPM is a better fit for the current research objectives.

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