Digital Health for Substance Use Disorder Treatment: Technology Acceptance by Drug and Alcohol Clinicians

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ABSTRACT

Substance use disorders (SUDs) represent a pervasive public health challenge worldwide, with Australia experiencing significant prevalence rates, which was accelerated during the COVID-19 era. Despite the pressing need for effective treatment strategies, a persist treatment gap persists, underscoring the imperative for accessible and comprehensive interventions. In response to this challenge, digital health interventions have emerged as promising tools to bridge this gap, offering innovative solutions to enhance treatment accessibility and efficacy. However, the acceptance and utilisation of these digital health tools among Alcohol and Other Drugs (AOD) clinicians play a pivotal role in their effectiveness.

The purpose of this study is to elucidate the motivations, barriers, and facilitators that shape the adoption of digital health tools in the context of SUD treatment. This multi-disciplinary study does so by integrating the technology adoption and digital health literatures. The research employs an exploratory sequential mixed-methods approach, integrating qualitative interviews and a quantitative survey followed by statistical analysis via Structural Equation Modelling.

This study makes a significant theoretical contribution by developing a model for the adoption and effective design and utilisation of digital health technologies in Substance Use Disorder (SUD) treatment environments. This model enables a comprehensive evaluation concerning the acceptability, feasibility, and clinically meaningful deployment of digital health technologies across drug and other drug clinicians grappling with substance-related health issues. Furthermore, it delineates strategies that facilitate the immediate implementation of interventions and the refinement of SUD treatment modalities by healthcare professionals. Given the rapid proliferation of digital health tools, new dilemmas have emerged, particularly concerning participant privacy

and equitable access to these technologies. Consequently, it is essential to integrate ethical frameworks that instruct clinicians on navigating daily practice and technology design, aiming to mitigate potential adverse effects on these populations, thereby preventing the aggravation of health disparities.

Furthermore, this study enhances its theoretical contributions by applying psycho socio-technical factors (clinicians' self-efficacy, clients ' equity and access, etc.) to understand the dynamic interactions between social systems and technological innovations within SUD treatment environments. This perspective facilitates a deeper analysis of how digital health tools are embedded within and influenced by existing social structures, norms, and practices, and vice versa. It encourages the examination of digital health technologies not merely as isolated interventions but as components of a larger ecosystem that includes end users' behaviour, policy regulations, and clients t engagement. This holistic view aids in identifying leverage points for systemic change, ensuring that digital health interventions are both technically sound and socially responsive, thereby maximising their potential to contribute positively to SUD treatment outcomes.

This interdisciplinary lens highlights the importance of considering a wide array of perspectives in designing, implementing, and evaluating digital health technologies, thereby enhancing their relevance, accessibility, and impact on individuals experiencing substance dependency. Furthermore, the study offers practical implications by proposing strategic solutions to support the integration of digital health practices. These solutions emphasise the importance of enhancing accessibility, quality, and efficiency in healthcare provision, particularly in the realm of SUD treatment.

In conclusion, this research provides a comprehensive understanding of digital health adoption dynamics among AOD clinicians in Australia. By addressing the complexities and nuances of digital health adoption, this study informs future research and implementation efforts aimed at improving outcomes for individuals and communities affected by SUDs. Through collaborative endeavours and strategic interventions, the transformative potential of digital health technologies in advancing SUD treatment and public health initiatives can be realised

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DECLARATION

I certify that this thesis: 1. does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university 2. and the research within will not be submitted for any other future degree or diploma without the permission of Flinders University; and 3. to the best of my knowledge and belief, does not contain any material previously published or written by another person except where due reference is made in the text.

Signed.....Lida shams .....

Date.....29//10/2024.....

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Abbreviations	Term
SUD	Substance Use Disorders-substance use dependence
ICT	Information and Communications Technology
AOD	Alcohol and other Drug
TAM	Technology Acceptance Model
TBI	Technology-Based Intervention
CAT	Computer-Assisted Therapy
BAI	Brief Alcohol Intervention
MI	Motivational Interview
CM	Contingency Management
MET	Motivational Enhancement Therapy
CRA	Community Reinforcement Approach
AOD	Alcohol or drug worker(s)
DHI	Digital Health Interventions

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The PhD was a journey of perseverance, and I am mindful of my personal dedication, growth and diligence in realising this achievement. It was a fulfilling experience which has prepared me for future accomplishments and is a testament to the importance of self-belief.

Lastly, I acknowledge the divine guidance that has illuminated my path. With deep appreciation, I look forward to the opportunities that lie ahead.

1. CHAPTER ONE - INTRODUCTION

1.1 Overview

This study examines the relationship between technology and substance use disorder (SUD) treatment, rehabilitation, and recovery. Specifically, it investigates the challenges associated with accepting digital health technology among treatment service providers in Australia. Despite the rapidly expanding literature on Information and Communication Technology (ICT) interventions in SUD, it remains unclear to what extent Alcohol and Other Drugs (AOD) workers in this field are adopting digital health. By exploring the intersections of technology and SUD treatment, this study aims to shed light on potential ways to enhance and optimise treatment outcomes in this field.

This chapter serves as an introduction to digital health topics for substance use disorder treatment, providing a rationale for the study's aims, objectives, and questions. The impact of this research, particularly on the social work and digital health disciplines, is presented from theoretical and practical perspectives.

1.2 Background to the Research

1.2.1 Substance Dependency

The consumption of illicit drugs is a significant global concern and can result in numerous health and social issues, including family disruption, violence, crime, and community instability (Merz, 2018). Addiction, or preferably substance use disorders (SUD) and substance use dependency, is characterised by compulsive substance-seeking behaviour and continued substance use despite its destructive consequences. It is a chronic and relapsing disorder that induces long-lasting changes in the brain and is considered both a complex brain disorder and a form of mental illness (Goldstein & Volkow, 2011; Sarmiento & Lau, 2020). Even after years of

abstinence, individuals remain at risk of relapse and returning to substance dependency (J. Menon & Kandasamy, 2018).

Illicit drug use is a significant global public health challenge, with around 230 million people, or 5% of the global population, having used such substances at least once. Of these, approximately 27 million (0.6%) are regular users. An estimated 15.9 million individuals inject drugs, potentially exposing 3 million to HIV, primarily through needle sharing. Furthermore, the World Health Organization highlights that about half the global population consumes alcohol, with usage rates ranging from 18% to 90% among men and 1% to 81% among women [i](Dasgupta, 2017). An estimated 284 million people used illegal substances in 2020, which is 30% more than in 2009; 11.2 million of them worldwide were injecting drugs (Canton, 2021). It is, directly or indirectly, responsible for 11.8 million deaths annually, more significant than the total number of cancer deaths (Dasgupta, 2017; Ritchie & Roser, 2019).

Based on statistics from the 2019 National Drug Strategy Household Survey (NDSHS), approximately 43% of individuals 14 years old and above in Australia have used illicit drugs (counting non-medical use of prescription drugs) at some point in their lives, while 16.4% have used them in the past 12 months (AIHW, 2020).

Between 2019 and 2020 in Australia, 121,274 substance-related seizures and 166,321 substance-related arrests were reported. Furthermore, 28.5 tonnes of illicit substances were seized, with methylamphetamine being the most seized and consumed illegal substance. Calculating the overall expenses of illicit drug usage in Australia is challenging. Nevertheless, experts have approximated significant annual expenditures related to methamphetamine ($5 billion), illicit and non-prescription substances ($15.8 billion), and cannabis ($4.5 billion) (S Whetton et al., 2020).

The COVID-19 pandemic has underscored the vulnerabilities of individuals with Substance Use Disorders (SUDs), highlighting the necessity for resilient healthcare frameworks in the post-

pandemic era. The ongoing analysis shifts towards understanding the pandemic's long-term effects on relapse risks and integrating these insights into future strategies for managing SUDs (Lowenstein et al., 2022; O'Dowd, 2020; L. Wang, Wang, Davis, Volkow, & Xu, 2022; Welle-Strand, Gjersing, Olsen, & Clausen, 2022). For a summary of the risk factors for COVID-19 affecting clients with substance dependency, see Appendix One.

Like other chronic health conditions, such as asthma, diabetes or heart disease, treatment for substance dependency generally is not a cure. However, substance use disorder is treatable and effectively managed (Kumar, Dangi, & Pawar, 2019; Pouletty, 2002).

The biopsychosocial intervention has effectively reduced substance use and its associated harms (Eastwood, Strang, & Marsden, 2017). However, though 3.56 million people suffer from SUDs, only 1 in 8 (14%) receive treatment as such. There is a critical need to improve this situation with investment in treatment required as well as increased accessibility through innovative approaches (World Drug Report, 2020) and, the gap in its treatment is a worldwide concern (Jacobson, Quist, Lee, & Marsch, 2023). However, the treatment gap fluctuates from 78% in developing countries to almost 50% in developed nations (Zewdu, Hanlon, Fekadu, Medhin, & Teferra, 2019).

The causes of the treatment gap vary from simple neglect and stigma to physical and psychosocial components, logistical obstacles such as limited availability and accessibility of service providers mainly in rural regions (Cunningham, Kypri, & McCambridge, 2011), and recruitment and retraining of qualified clinicians (Matthew R McGrail, Humphreys, Joyce, Scott, & Kalb, 2011). These barriers could differ depending on the category of substance, clients' characteristics, and service providers. The connection between investment in substance treatment and reduction in substance use, overdose, and crime is well established. For example, based on even conservative estimates, for every $1 spent on substance treatment, between $4 and $7 is saved in robbery and substance-related criminal justice costs. If healthcare-related

expenses are included, total savings can be as high as 12 to 1 (Ettner et al., 2006; SAMHSA, 2016; Voce & Sullivan, 2022).

Reduced workplace conflicts, better efficiency, and fewer substance-related accidents are some benefits shown in research (Abuse, 2018; McLellan & Woodworth, 2014). Moreover, evidence-based treatment modalities are available to address distinct aspects and challenges of SUD. Thus, there is a vital need to establish and employ new treatment delivery systems to improve the accessibility and affordability of SUD treatments.

1.2.2 Information and Communication Technology in Healthcare

As technology continues to advance, it has significantly impacted and transformed various aspects of our daily lives. The emergence of faster, portable, and highly powered multi-functional devices such as smartphones and computers has revolutionised how we interact, work, and conduct our businesses.

As of January 2024, internet users worldwide reached 5.35 billion, accounting for sixty-six per cent of the worldwide population. Between them, 5.04 billion individuals were active on social media platforms, representing almost 62.3 per cent of the world's residents. Furthermore, this figure is projected to increase by 860.7 million between 2023 and 2028 (Digital, 2024).

Technology has transformed the landscape of healthcare delivery, including treatment for substance use disorders (SUDs). Despite the growing trend of using the Internet for illegal substance-related activities (Bisen & Deshpande, 2018), there is increasing evidence of online information and resources targeting treatment, recovery, and substance dependency rehabilitation. Moreover, technology-oriented intervention programs have become the mainstream treatment modality globally, including CBT4CBT in the United State (Kelpin, Parlier-Ahmad, Jallo, Carroll, & Svikis, 2022), SMART Recovery (Bliuc, Best, Iqbal, & Upton, 2017) and Hello Sunday Morning in Australia (Carah, Meurk, & Hall, 2015).

In SUD treatment, as this thesis will establish, treatment can be successful, yet many individuals face ongoing challenges that heighten their risk of relapse, such as genetic factors, interpersonal issues, psychiatric comorbidities, employment difficulties, and neurocognitive deficits(McKay, Franklin, Patapis, & Lynch, 2006). Recovery-enhancing factors, such as supportive social networks, interests that support abstinence, improved coping skills, and employment, require time and sustained support. This explains the limited long-term success of acute care models, as relapse risk remains high after the typical 3 to 6-month treatment period. Effective management requires extended patient engagement to address waning motivation, cravings, reduced self-help participation, neurocognitive limitations, and stress vulnerability. Ongoing care and support programs like Alcoholics Anonymous are crucial for long-term recovery, though consistent participation is uncommon (Marcu, Ondersma, Spiller, Broderick, Kadri, & Buis, 2022).

Digital interventions have gained popularity in addressing SUD challenges. Reviews [25,26] show a complex landscape of target users, usage patterns, and effectiveness. These interventions offer personalized, accessible support that complements traditional treatments (Tofighi, Nicholson, McNeely, Muench, & Lee, 2017).

There is a strong link between high-quality SUD treatment outcomes and excellent digital health. Digital health tools in SUD treatment has shown promising results in decreasing alcohol and depression symptoms, improving quality of life, and increasing client satisfaction, accessibility, and cost-effectiveness (Kruse, Lee, Watson, Lobo, Stoppelmoor, & Oyibo, 2020). Furthermore, it can facilitate engaging clients who resist face-to-face communications while addressing the stigma associated with SUD by offering confidentiality and anonymity (Barker & Barker, 2022). Additionally, digital health tools can be available 24/7 and accessed in times of crisis, making them a valuable resource (Kshirsagar, Morris, & Bowman, 2017).

Real-time longitudinal patient data can guide diagnosis and treatment decisions or facilitate timely interventions before a crisis develops. Remote on-demand provision of therapy allows for more consistent and accessible treatment. Objective measures of medication adherence allow for better-informed treatment decisions (Batra, Baker, Wang, Forma, DiBiasi, & Peters-Strickland, 2017).

This thesis acknowledges that technology does not entirely seek to replace traditional treatment approaches. Instead, it argues that technology allows for the complementary use of various innovative tools, which expands the limited number of therapeutic styles available for treating substance dependency. In addition, strategies for managing SUDs should be capable of addressing the chronic and relapsing nature of dependency. E-tools can provide valuable support in meeting these challenges.

Also, digital health technology includes education, rehabilitation support programs, health and wellness monitoring, ICT-assisted behavioural treatments, and information and resources for prevention. Furthermore, it can be accessed through various methods, such as phone counselling and video conferencing platforms, self-service desktop therapeutic tools, internet-based text messages (e.g., email, chat, and forums), as well as s-Health (smartphone health) or m-Health (mobile health). Therefore, it is argued that successfully integrating and implementing E-tools into traditional face-to-face treatment approaches can transform the quality and effectiveness of service delivery.

1.3 Research Topic

The behavioural intention of AOD clinicians to use technology is crucial for successful implementation, service quality, and treatment outcomes. However, despite advancements in

healthcare technologies, this does not necessarily translate into corresponding advances in clinicians' practices or beliefs (Patrick et al., 2016; Schueller, Washburn, & Price, 2016).

E-platforms are rarely integrated or sustained, especially those requiring significant changes in organisations or broader care systems (Lau, Price, & Keshavjee, 2011). As a result, it is common for intended users to reject or not accept them. Additionally, clinicians' acceptance of e-interventions is the most critical aspect in determining the success or failure of new technology-supported services at a local level (Greenhalgh et al., 2017). In other words, the success of e-tools is determined on the work floor.

Thus, understanding how AOD clinicians implement and accept digital health and their advantages and concerns is crucial for ensuring these tools reach clients. However, despite growing evidence of the potential benefits of digital health technology for SUD treatment, the slow and complex issue of acceptance by AOD workers, social workers, practitioners, and other clinicians is slow and complex; hence, this thesis explored this phenomenon.

1.3.1 Research Aims and Objectives

This study explores the primary factors influencing the acceptance of digital health by AOD clinicians working in any SUD treatment, recovery, and rehabilitation setting in Australia. The specific objectives of this study included:

1. To identify the challenges that hinder the use and acceptance of digital health by AOD clinicians in Australia.
2. To identify effective strategies to improve clinicians' acceptance and sustained use of digital health in the SUD field and social work practice more broadly.

1.3.2 Research Questions

Primary Research Question:

What are the key factors influencing clinicians' use and acceptance of digital health technologies in the treatment of SUDs in Australia?

1.4 Scope of Study

This scope of the research had three main demarcations: the research area, the research literature, and the research industries, as explained below.

1.4.1 Demarcation of the research area – Digital Health

Researchers and digital health specialists have proposed diverse potential technologies for behavioural health care (Bauer, Thielke, Katon, Unützer, & Areán, 2014; Drissi, Ouhbi, Marques, de la Torre Díez, Ghogho, & Janati Idrissi, 2021). However, this research focused on the most prevalent and developed therapeutic digital health tools for clients who have initiated treatment with a SUD service provider. Based on the patient-facing technology model, there are four main classifications of technology that individuals may encounter in the context of behavioural healthcare (Barak, Klein, & Proudfoot, 2009) See Figure 1.

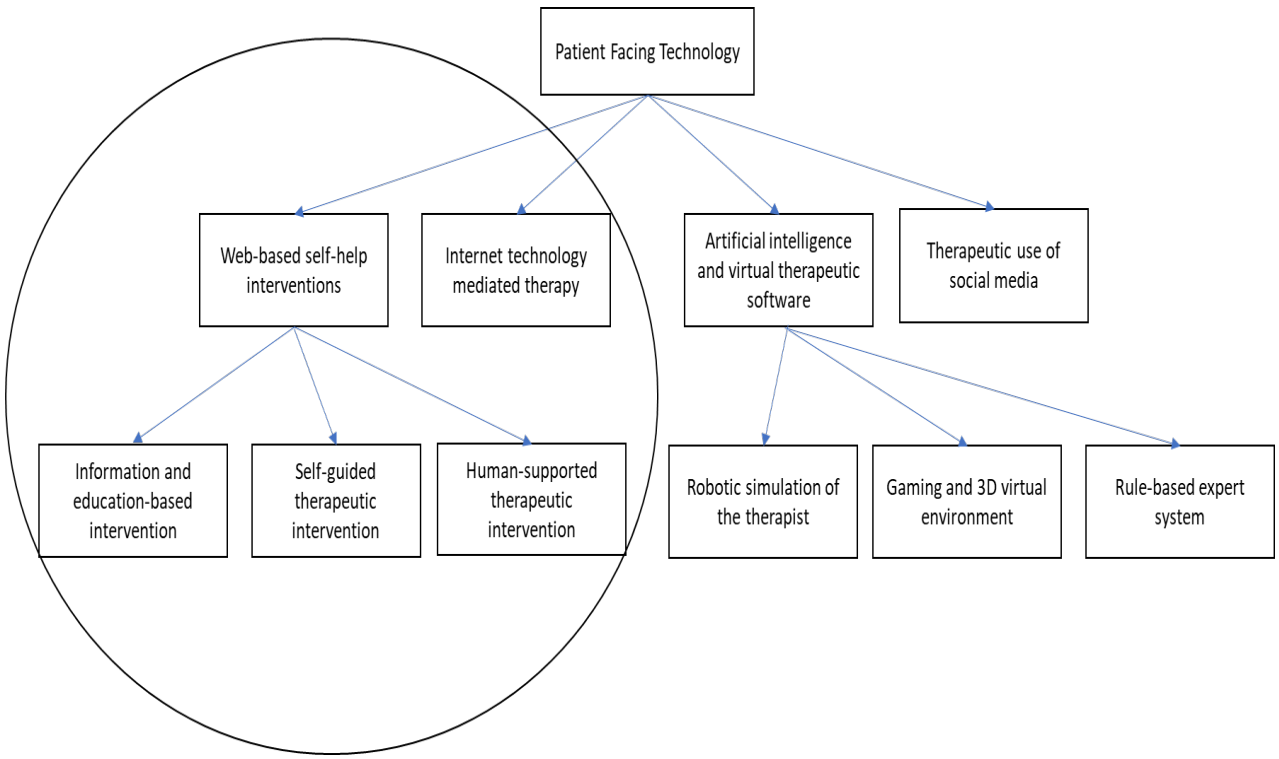

Figure 1- The Classification of Patients Facing Technology (Barak, Klein, & Proudfoot, 2009).

This research mainly focused on the following two categories: They are the most developed and used ICTs and can more directly deliver treatment for SUD.

Web-based self-help interventions, stand-alone interventions that offer clients evidence-based therapeutic materials, and Internet-medicated therapy (online counselling) can be used self-reliantly.

1.4.2 Demarcation of the Literature -Technology Acceptance

Acceptance described as “an antagonism to the term refusal and means the positive decision to use an innovation” (Simon, 2001, p. 179). For decision-makers, understanding the factors that influence users' choices to engage with a particular system is crucial, as this knowledge can inform the design process. Both practitioners and researchers frequently inquire into the reasons behind individuals' acceptance of new technologies. Addressing this inquiry can lead to improved methods for designing, evaluating, and anticipating users' responses to technological innovations (Taherdoost, 2018).

Technology adoption encompasses the processes of accepting, integrating, and fully embracing new technological advancements. The initial phase, known as technology acceptance, involves developing a positive attitude toward the technology, which is shaped by multiple influencing factors. As articulated by Rogers in his Innovation Diffusion Theory (1962, 1995), adoption represents the deliberate decision to utilize a technological innovation to its fullest extent, recognizing it as the most advantageous option available (C. R. Rogers, 1995).

In this thesis, the terms technology acceptance and adoption are used interchangeably, reflecting their close connection. The critical factor in adoption is the adopter's perception of the technology, which, in the context of this research, refers to AOD clinicians. This perception ultimately determines their decision to embrace and integrate the innovation.

More, Research focusing on information technology in public health often emphasises the design and operation of digital health solutions rather than examining how end-users interact with and respond to existing digital tools (Holden & Karsh, 2010; Hossain, Yokota, Sultana, & Ahmed, 2019). However, this research is crucial in evaluating current end-user experiences, trends, and perceptions of digital health. Supplying a solid foundation of clinicians' technology acceptance informs future research and guides the improvement of digital health solutions for clients experiencing substance dependency. It argues that for any promising novel digital interventions, their usefulness should be assessed based on their capacity to enhance the delivery of the client's outcome. This requires balancing the potential advantages of e-tools against several possible countervailing effects, including the quality of care, privacy, implementation cost, and uptake (Breslau & Engel, 2015), as detailed in Figure 2.

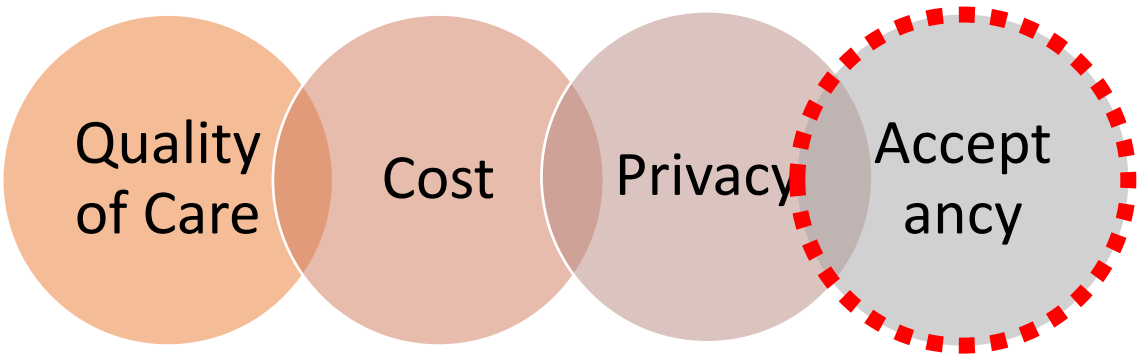

Figure 2- Main Challenges Associated with Digital Health Adoption (Breslau & Engel, 2015).

This study specifically examines the uptake of digital health, referred to as "clinician technology acceptance" or "clinician technology adoption," within substance use disorder (SUD) settings. The focus is on clinicians' acceptance and adoption for two primary reasons.

First, AOD clinicians act as the end-users of e-tools, which means they must decide whether to engage with these tools. Second, as clients rely on practitioners' professional judgment and

clinical resources, AOD professionals effectively serve as gatekeepers of clinical knowledge. Therefore, it is posited that understanding the interests, needs, and concerns of AOD professionals is crucial for the productive integration of digital tools within the clients' care system.

The terms "clinicians," "practitioners," and "workers" are employed throughout the thesis to encompass a diverse group of professionals working in SUD settings, including, but not limited to, drug and alcohol workers, AOD workers, social workers, Family counsellors, Rehabilitation Counselors, Psychologists, and others.

1.4.3 Demarcation of the industries – SUDs Treatment

As the study emphasised, SUD is a chronic disease marked by a relapsing cycle. Unlike casual use or dependence, addiction involves persistent drug-seeking and use despite reduced pleasure and profound consequences for the quality of life and well-being (O'Brien, 2011). Following the DSM-5 definition, this thesis investigates SUDs involving illicit and legal substances like nicotine, alcohol, and prescription drugs. These disorders are classified on a severity scale from minor to severe, with the most common SUDs featuring one or more of the substances above (DSM-5, 2022).

- Alcohol (beer, wine)
- Opioids (heroin)
- Sedatives, hypnotics, anxiolytics
- Stimulants (amphetamines, methamphetamines, cocaine)
- Hallucinogens (Ecstasy, PCP, LSD, psilocybin mushrooms, peyote, mescaline)
- Cannabis/marijuana
- Nicotine (tobacco)
- Inhalants (petrol)
- Other/unknown.

Our study is centred explicitly on substance use disorder treatment, adhering to the Continuum of Care model. This comprehensive, integrated care system encompasses promotion, prevention, treatment, and recovery, as (Evashwick, 1989) illustrated in Figure 3.

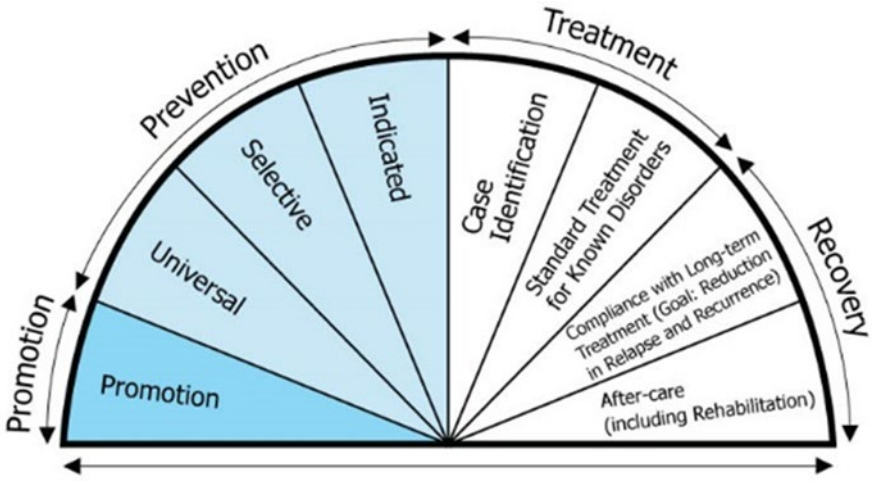

Figure 3- The Continuum of Care Model (Evashwick, 1989).

Treatment for Substance Use Disorders (SUDs) is a purposeful journey of self-restoration, wherein recovery capital is used to manage drug effects, control substance use, enhance well-being, and pursue life goals (Inanlou, Bahmani, Farhoudian, & Rafiee, 2020).

Research on substance therapy and rehabilitation typically categorises treatment programs into modalities such as pharmacotherapies or behavioural therapies. Generally, treatments commence with detoxification, or “medically managed withdrawal” (primary treatment), progress to individual or group counselling (secondary treatment), and conclude with residential treatment and additional supportive services (tertiary treatment) (Deneke, Knepper, Green, & Carnes, 2015). Detoxification, although often the initial step, fails to address social, psychological, or behavioural issues, thereby seldom leading to enduring change. However, counselling remains the most prevalent treatment, utilised by 37% (AIHW, 2022a). Given this, our focus is on substance dependency treatments’ secondary and tertiary levels.

Consequently, the present study concentrates exclusively on clinicians in Australia who engage with all nine categories of substances across the entire spectrum of dependency levels, employing digital health tools within a diverse array of treatment delivery settings.

1.5 Significance / Contribution of the Research

1.5.1 Social Work

Substance use dependency treatment is identified as a primary practice area within the social work discipline, and it is progressively needed to treat individuals with SUD (Wells, Kristman-Valente, Peavy, & Jackson, 2013). On the other hand, information and communication technology (ICT) has notably impacted nearly all human service disciplines; however, social work has experienced a slower adoption of technology than other professions (Berzin, Singer, & Chan, 2015). This limited research on digital health use in social work hinders the widespread and sustainable adoption of e-interventions. Moreover, the existing body of research on incorporating technology into practice primarily originates from psychology and counselling rather than social work (Singer & Sage, 2015). For instance, in a systematic review of digital health-assisted social work intervention, out of 17 included papers, only three assessed the role of e-tools in the intervention(C. Chan & Holosko, 2016). Thus, the comparatively slower uptake of digital health in social work may impede their ability to treat clients with SUD effectively.

Clinicians' acceptance, adjustment, and empathic and sympathetic perceptions play crucial roles in the treatment process. In addition, ensuring confidentiality and privacy and addressing legal and ethical issues related to verifying a patient's identity can significantly influence the client's engagement and the overall efficacy of the treatment outcome.(Miller & Moyers, 2015; Perle et al., 2013). Subsequently, therapists, social workers, and other clinicians must acquire new technical skills and adhere to standards that enable them to achieve 'virtual intimacy' and establish a solid therapeutic alliance with clients within the virtual landscape.

Hence, his research addresses the limited literature on digital health in social work practice, emphasising the significance of digital health acceptance in social work interventions for SUD treatment.

1.5.2 ICT Field

The importance of human-centred design technologies in healthcare has become increasingly explored. Successful use of technology does not simply occur due to its availability. Both an understanding of the technology and experience in using it for instructional purposes is crucial for effective implementation (Reeves et al., 2020).To achieve effective integration between people, technology, and practice, success depends on individuals who can anticipate transformations, shifting roles, and adaptations of technology. Furthermore, it relies on those who can manage new errors and complexities associated with technology (Fossa, Bell, & DesRoches, 2018; Woods & Dekker, 2000). Successful implementation of digital health in SUD by clinicians requires understanding, experience, anticipation, management, and innovation.

For these reasons, this study focused on the acceptance and uptake of digital health by clinicians already working in the field and incorporating digital health into their daily work. It is argued that those actively engaging with digital health can provide unique insights into the critical factors shaping the adoption of ICT.

1. What are the prevailing practices and trends in the integration of digital health technologies by clinicians managing SUDs in Australia?

2. Which theoretical framework most effectively elucidates the determinants of clinicians' acceptance and utilization of digital health technologies in the context of SUD treatment?

3. What are the perceived advantages and challenges associated with the use of digital health technologies in SUD treatment from the perspective of clinicians?

4. What evidence-based strategies can be developed to enhance clinicians' acceptance and effective implementation of digital health technologies in SUD treatment?

5-How can strategies for increasing clinicians' acceptance of digital health technologies be adapted and applied to related disciplines, such as social work and public health, to foster broader adoption?

1.6 Summary

This chapter aimed to figure the fundamentals of the study issues. A review of the study literature and context revealed the main reasons for SUD "treatment gap" clinicians as "key stakeholders" in Australia for this study. The importance and scope of research in ADO clinicians' acceptance of digital health were explained. Furthermore, the study objectives, which determined the construction of research questions and highlighted the significant contributions, were also addressed.

CHAPTER 2.0 LITERATURE REVIEW

2.1 Overview

This section establishes the main problems surrounding digital health in addressing SUD, especially concerning its acceptance by AOD workers in Australia. This contributes to identifying the current practice of e-intervention to report the critical challenges of acceptance and answer the first research question: What is the current state of digital health use in SUD treatment in Australia?

To achieve this, the chapter discusses ICT in healthcare, presenting key definitions and identifying digital health categories in Section 2.2. It then defines important digital health terminology in the SUD setting, outlines advantages and challenges, provides a critical

perspective of digital health tools and platforms in SUD, discusses limitations, Section 2.3. The benefits of digital tools are discussed in Section 2.4, along with the treatment modalities and how clinicians utilise digital technology in practice. Section 2.5 explains the study's focus on clinicians and explores substance harm, substance treatment, and the AOD workforce in Australia. Finally, a summary is provided in Section 2.6.

Additionally, in the upcoming chapters, the literature review will be structured to address the following sub-questions.

1. What are the prevailing practices and trends in the integration of digital health technologies by clinicians managing SUDs in Australia?

2. Which theoretical framework most effectively elucidates the determinants of clinicians' acceptance and utilization of digital health technologies in the context of SUD treatment?

3. What are the perceived advantages and challenges associated with the use of digital health technologies in SUD treatment from the perspective of clinicians?

4. What evidence-based strategies can be developed to enhance clinicians' acceptance and effective implementation of digital health technologies in SUD treatment?

5-How can strategies for increasing clinicians' acceptance of digital health technologies be adapted and applied to related disciplines, such as social work and public health, to foster broader adoption?

By addressing these sub questions, this thesis will provide an in-depth analysis of the role and impact of digital health technologies in SUD treatment.

2.2 ICT in Health Care

Undoubtedly, digital tools are transforming the way the healthcare system functions. The list of promising digital solutions is promptly expanding. In addition to “video consultations,” email, mobile apps, wearable devices, chatbots, AI-powered diagnostic tools, voice-controlled systems, and mobile sensors, behavioural activity monitoring is also accessible (Ramsetty & Adams, 2020).

Numerous countries and organisations are increasingly focusing on digital health, leading to a significant rise in the release of health policies and reports, such as the World Health Organization’s Global Strategy for Digital Health (WHO, 2021).

Existing studies indicate that digital health is now capable of empowering clients to become knowledgeable and active participants in their healthcare systems by developing their social support network, skills, and activities, as well as succeeding in the daily challenges associated with their health conditions (Baudendistel et al., 2015; Choun & Petre, 2022). In addition, service providers can enhance healthcare services electronically, reducing the impact of time, space, and remoteness (Tangcharoensathien, Witthayapipopsakul, Panichkriangkrai, Patcharanarumol, & Mills, 2018). Thus, digital health can potentially empower us as a society by improving healthcare access and outcomes and enabling individuals to take a more active role in managing their health.

However, with the expanded role of ICT, several technological challenges have intensified, including information security, client privacy, effectiveness, accessibility, compatibility, and digital health acceptance within the existing healthcare system (Golinelli, Boetto, Carullo, Nuzzolese, Landini, & Fantini, 2020). Therefore, digital health acceptance is the primary focus of this study.

2.2.1 ICT Definition and Categories

Information and communications technology (ICT) or information technology (I.T.) significantly affects our professional lives, revolutionises our communication methods, and influences how

governments provide social services. However, the complexity of defining ICT is a widespread challenge, and the rapidly evolving nature of ICT could be a contributing factor. For instance, “technology” initially referred to hardware; however, it has grown to encompass hardware and software components over the years.

ICT is a mixture of two components: 1) “information technology” (I.T.) and 2) “communication technology” (C.T.). These terms encompass tools, devices, and equipment such as computers, laptops, scanners, digital cameras, and software that enable users to “access, retrieve, store, organise, manipulate, and present information through electronic means.” (Zhao, Lei, & Conway, 2006, p. 685). Therefore, in this study, ICT is defined as digital information and communication devices, tools or platforms that help clinicians and/or clients in treatment, recovery, and substance dependency rehabilitation. This encompasses but is not restricted to, web-based self-help tools and online counselling services. Thus, these platforms do not exist independently but support individuals engaging and interacting within the digital world.

2.2.2 Digital Health

This section briefly introduces the range of ICT tools and strategies implemented in public healthcare, focusing on SUDs. There is considerable conceptual confusion regarding ICT terminology in the academic literature. Terms such as digital health, telehealth, eHealth, mHealth, e-intervention, and technology-based intervention. These terms are often used interchangeably, with various definitions existing based on their specific contexts (S. Martin, Kelly, Kernohan, McCreight, & Nugent, 2008).

However, nowadays, the term ‘digital health’ is often employed as a comprehensive umbrella term that includes eHealth and emerging areas such as applying computing sciences (in fields like “big data,” genomics, and artificial intelligence, for instance). Digital health is the integration of digital technologies, like artificial intelligence, the Internet of Things, big data, and robotics, into health practice to enhance patient care, involving a wide array of smart devices and users (WHO, 2021). Figure 4 illustrates the main categories of ICT in healthcare, and the key terms will be defined and clarified in Sections 2.3.2 through 2.3.9.

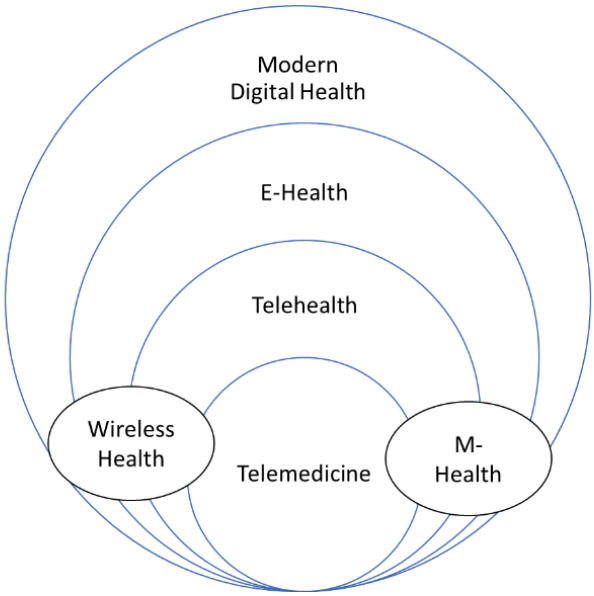

Figure 4 Modern Digital Health Categories

2.2.3 E-Health

John Mitchell's 1999 definition of e-health marked a pivotal moment, conceptualizing it as the integration of electronic communication and information technology in healthcare. This approach includes using digital data for clinical, educational, and administrative functions, enhancing healthcare delivery's efficiency, accessibility, and quality. E-health merges technology with healthcare practices, facilitating services like telemedicine and electronic health records, thereby expanding healthcare access. Mitchell's foundational work has been instrumental in driving the

modernisation of healthcare systems through digital innovations (Mitchell, 1999). The World Health Organization (WHO) describes e-health as the efficient, safe application of ICT in health-associated areas, encompassing healthcare services, health monitoring, health education, knowledge and research. This represents various services or systems intersecting health, technology, and societal domains (WHO, 2023). In a broader sense, “the term not only technical connotations but also a state of mind, a way of thinking, an attitude, and a commitment for networked, global thinking to improve healthcare locally, regionally, and by using information and communication technology” (Eysenbach, 2001, p. 20). Ultimately, e-health aims to enhance the accessibility of integrated care for positive behaviour change. As such, social components play a crucial role in its successful implementation.

2.2.4 Telehealth and Telemedicine

Telehealth encompasses the provision of healthcare services from a distance. It leverages (ICTs) to supply healthcare services to clients and providers who are geographically separated. This approach enhances access to quality, cost-effective healthcare services, benefiting individuals in remote locations, vulnerable populations, and aging communities. Through telehealth, patients can receive diagnoses, treatment, research, and ongoing education from health professionals, regardless of physical location (Sood et al., 2007). Telemedicine, which refers to “healing at a distance” (WHO, 2010, p1o), is a synonym for telehealth. However, it has developed into telehealth, which is frequently considered to have a broader scope encompassing health promotion and disease prevention. Video consultations are one of the popular platforms within telehealth.

2.2.5 M-Health

Mobile health, also known as m-health, refers to providing public and medical care services carried by mobile devices, such as mobile phones, client monitoring devices, personal digital assistants, and other wireless tools or devices. Recently, smartphone apps have become more widespread and have been designed to manage chronic conditions, medications, referrals, and

training. It is a rapidly emerging area in modern healthcare with extensive capabilities (Areàn, Hoa Ly, & Andersson, 2022).

2.2.6 Wearable Devices

Wearable devices, such as the Apple Watch and Fitbit, wristbands, and bio-energy patches, have recently gained popularity. These devices monitor individuals' mental and physical health, including stress, heart, oxygen, and sleep patterns. The primary goal of wearable devices is to enhance users' overall health, which, in turn, may contribute to a reduction in general healthcare costs (Thilakarathne, Kagita, & Gadekallu, 2020).

2.2.7 Virtual Reality (V.R.)

Virtual Reality (V.R.) is an innovative human-computer interface that enables users to engage with and become entirely realistically immersed in a computer-generated environment (Eichenberg & Wolters, 2012). By creating an artificial environment on a headset or computer using visual, auditory, or other sensory modalities, V.R. allows users to experience a fully immersive setting (Aukstakalnis, 2016). Consequently, V.R. has the probable to significantly enhance the healthcare system and supply valuable education for clients, medical staff, and clinicians.

2.2.8 Medical Internet of Things (MIOT)

The Internet of Medical Things (IoMT) is an emerging healthcare technology that involves dynamic network frameworks and internet-connected devices designed to capture vital physical parameters in clients. These devices help identify pathological factors through compact ICT devices (Dimitrov, 2016). Such innovations include wearable biosensors, smart thermometers, and virtual hospitals. MIoT tools capture, interpret, and distribute health data, linking patients to physicians and enabling the secure transfer of medical data, reducing hospital visits and alleviating pressure on healthcare systems (Akhtar, Rahman, Sadia, & Perwej, 2021).

2.2.9 Artificial Intelligence (A.I.)

A.I. encompasses a variety of techniques, including deep learning and machine learning, where algorithms generate and analyse data. An algorithm is a consistent process for solving problems. Deep learning depends on multiple data sets to represent complex relationships between inputs and information outputs. In healthcare, A.I. proves beneficial for clients' care analytics, population health, drug development and precision, automated workflow systems, and supporting clinical decisions, even though interpreting the results can be challenging for experts (Panch, Szolovits, & Atun, 2018). Examples include AI-assisted robotic surgeries, virtual nurses, and medical image analysis.

2.2.10 Social Media

Social media platforms, such as Facebook, Twitter, and Instagram, can be described as a collection of internet-based apps that enable creating and exchanging user-generated content (A. M. Kaplan & Haenlein, 2010). Service providers or clients can utilise social media to disseminate information, navigate resources, engage with and educate clients, significantly younger and at-risk individuals, discuss health policies and promote healthy behaviours (Welch, Petkovic, Pardo Pardo, Rader, & Tugwell, 2016).

2.2.11 Summary

The healthcare system rapidly adopts emerging digital solutions such as wearable devices, telehealth, virtual reality, and artificial intelligence. This shift towards digital health has the potential to empower people to take an active role in controlling their health and improve healthcare access and outcomes, though it also presents several technological challenges.

2.3 Digital Health in SUD Setting

Given the escalating burden of mental illnesses, including SUD, across countries—with a projected cost of $16 trillion to the global economy by 2030 (Patel et al., 2018), there is an important need for invention to ensure more efficient, equitable, and appropriate access to treatment services. This need for innovation is further emphasised, considering that substance dependency is intrinsically defined by intricate biopsychosocial factors, which inherently complicate the treatment of SUDs. Consequently, the field grapples with significant challenges, such as identifying suitable service providers and recruiting and retaining proficient clinicians, thus substantiating the complexity of managing SUD (M. R. McGrail, Wingrove, Petterson, Humphreys, Russell, & Bazemore, 2017).

Nonetheless, digital health can potentially address the challenges associated with the equitable delivery of evidence-based psychological treatment. Various tools such as text messages, video consultations, smartphone apps, virtual reality (V.R.), and web-based self-help tools have been applied in SUD treatment settings. On the other hand, some critics argue that digital tools may not be suitable for clinical interventions due to concerns regarding privacy and cost. Significantly, the COVID-19 pandemic has catalysed the prompt adoption of digital and online platforms beyond healthcare systems. These platforms had formerly been underutilised despite their wide accessibility and demonstrated efficiency (Pierce, Perrin, Tyler, McKee, & Watson, 2021).

The subsequent section, Section 2.3.1, defines key terminology and distinctions. The following sections will delve into the main advantages and challenges of implementing and utilising digital health for therapeutic purposes in SUD treatment, capped off by a critique that highlights limitations.

2.3.1 Key Terminology and Differences

Not everyone using or misusing substances becomes dependent or experiences substance use disorders. However, substance use, misuse, and disorders should be viewed as a spectrum, as demonstrated in Figure 5 adopted from (Soni, Sharma, Khinchi, Gauttam, & Gauttam, 2017). Characteristically, substance use disorders develop slowly over time due to repeated harm, leading to changes in the brain.

Multiple factors, such as the category of substance, genetic predispositions, and the severity of misuse, effect whether and how quickly a person might foster a substance use disorder. Understanding these differences can assist us in determining the appropriate level and style of intervention.

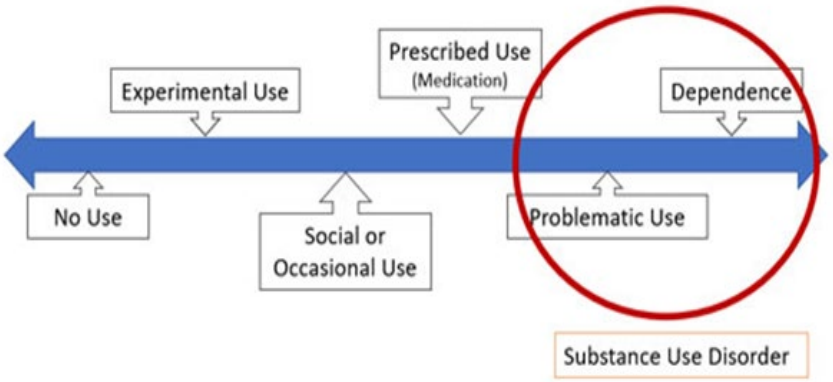

Figure 5 Substance Use Disorder Spectrum (Soni et al., 2017)

This study defines key terms related to substance use (DSM–5, 2013); see Table 1 for the Criteria for Diagnosing SUDs.

- Substance: A psychoactive compound with potential health/social impacts. It can be legal (tobacco, alcohol), illegal (ecstasy, cocaine), or medically controlled (Oxycontin, Vicodin).
- Substance Use: The use of any substance, even once.
- Substance Misuse: Risky, inappropriate use of a substance.

- Substance Use Disorders (SUD): Disorders from mild to severe that involve chronic, compulsive drug taking.
- Recovery: Overcoming dependence and reintegrating into society.
- Relapse: Return to drug use after an attempt to stop.
-

Table 1 Criteria for Diagnosing SUDs.

1	Using in more significant amounts or for longer than intended
2	Wanting to cut down or stop using but not managing to
3	Spending a lot of time to get, use, or recover from use
4	Craving
5	Inability to manage commitments due to use
6	Continuing to use it, even when it causes problems in relationships
7	Giving up important activities because of use
8	Continuing to use it, even when it puts them in danger
9	Continuing to use, even when physical or psychological problems may worsen
10	Increasing tolerance
11	Withdrawal symptoms
Fewer than 2 symptoms = no disorder; 2-3 = mild disorder; 4-5 = moderate disorder; 6 or more = severe disorder (DSM–5, 2013).	

2.3.2 Advantages of Digital Health in SUDs

Digitally-based therapeutic tools present a multifaceted solution to several pressing issues in mental health care. First, they can offer cost-effective treatment to many clients, thus improving accessibility (Marwaha, Landman, Brat, Dunn, & Gordon, 2022). Furthermore, by promising confidentiality and anonymity, these tools can help alleviate the stigma often associated with mental health treatment (Riper & Tait, 2013). Additionally, these digital aids play a vital role in reaching specific populations that may be disengaged by traditional treatment methods (Ma, Chan, & Chen, 2016). Notably, this includes individuals residing in rural areas where access to mental health care is limited due to scarcity of resources and the presence of stigma (S. Chan, Markoulakis, & Levitt, 2023; Porfilio-Mathieu, Pigeon-Gagné, Dagenais, & Ridde, 2022).

Thus, digitally-based therapeutic tools represent an innovative and practical approach to expanding mental health care reach and engagement.

Moreover, e-tools can generate automated information characterised by high standardisation. This level of uniformity may not always be attainable through traditional face-to-face interventions. Significantly, such standardisation can facilitate data collection, enable a thorough analysis, and provide invaluable raw data for researchers (Castaneda et al., 2015; Ibrahim, Liu, Zariffa, Morris, & Denniston, 2021)]. Therefore, digital therapeutic tools are crucial for reaching traditionally under-served populations and are instrumental in advancing research and more effective treatments.

Digital health, in particular, has shown tremendous potential for substance use disorder (SUD) treatments. A systematic review of the literature revealed that digital tools, regardless of the treatment method, led to clinically significant improvements in clients with alcohol use disorder in seven out of the eight studies evaluated (Fowler, Holt, & Joshi, 2016). This improved treatment efficiency suggests many opportunities to enhance care service delivery (McDonnell, MacNeill, Chapman, Gilbertson, Reinhardt, & Carreiro, 2021).

A significant body of evidence supports the development and application of digital health in treating substance use disorders (SUDs). Adopting such technology is poised to allow providers to implement evidence-based, more effective, scalable, and easily accessible programs. Given its portability and flexibility, e-tools are anticipated to address at least four primary limitations of the existing substance treatment system: Quality of Care, Access to Care, Treatment Dropout,

and Treatment Stigma, as illustrated in Figure 2.3.

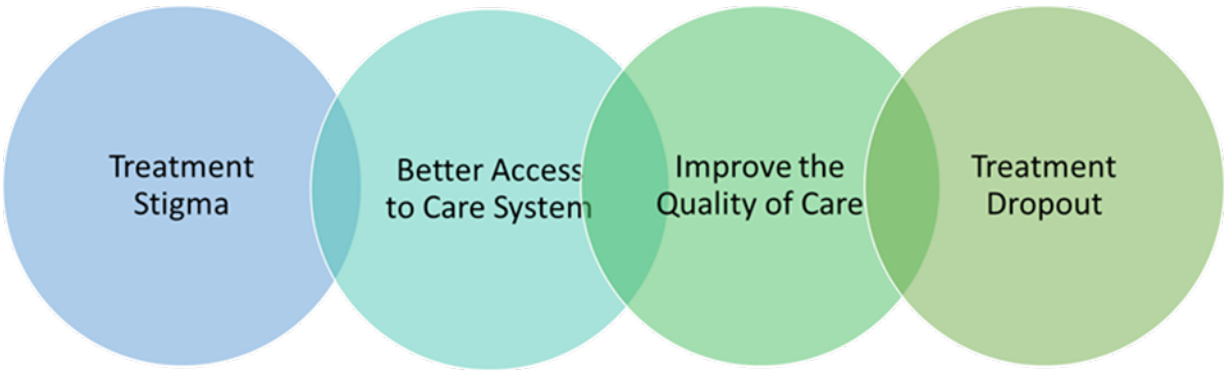

Figure 6 The Four Main Aspects of SUDs Treatment Address with Digital Health

2.3.3 Challenges with Digital Health in SUDs

Evaluating the effectiveness of digital health interventions, like any promising e-health intervention, requires assessing their ability to enhance the existing care system and discovering a balance between the benefits of digital health and potential adverse effects is essential. Despite the increasing number of e-tools for substance dependency, uncertainties persist regarding the mechanisms, conditions, and specific features that influence their efficacy (Perski, Baretta, Blandford, West, & Michie, 2018; Shahab & McEwen, 2009; Srivastava, Chaudhury, Dhamija, Prakash, & Chatterjee, 2020).

This section will explore the drawbacks and concerns associated with digital interventions. While digital health initiatives can potentially improve the quality of care, concerns arise regarding their ability to maintain this quality level consistently. For example, many self-guided websites and smartphone applications primarily offer information and promote treatments, making it challenging to evaluate the reliability of the provided information or the effectiveness of these tools. Additionally, the extent to which digital health initiatives enhance service accessibility depends on the existing care system rather than on the e-tools themselves (Breslau & Engel, 2015).

Moreover, while trusted professionals develop specific digital platforms, many others lack credibility and may not adhere to evidence-based methodologies, security guidelines, or stakeholder involvement during the development of e-tools. Additionally, numerous other factors, including treatment motivation, self-efficacy, and consistent engagement, can significantly impact the outcome (Aljedaani & Babar, 2021; Bozdağ & Çuhadar, 2022). The security of collected personal information and data in cyberspace is indeed a complex challenge. In the context of e-health, particularly in substance dependency, ethical and privacy concerns are raised for researchers, clients, and clinicians (Hamideh & Nebeker, 2020; Marsch et al., 2020). Additionally, platforms such as social media, while facilitating communication between consumers and suppliers, expose clients to substance use risks (Bakken & Demant, 2019).

The effectiveness of online or blended therapy may raise questions in some instances. A range of factors, such as facial expressions, voice characteristics, and body language, play a crucial role in our communication. However, the virtual environment presents a challenge by eliminating three vital components of the therapeutic relationship: face-to-face interaction, verbal communication, and synchronous communication (Fenichel et al., 2002). Moreover, some substance use disorder (SUD) treatments inherently require clinicians to introduce challenges and confrontations to foster the therapeutic relationship actively (Hardy, Cahill, & Barkham, 2007). The shift to online therapy can potentially affect the exchange of signals between clients and clinicians, virtual intimacy, and overall client outcomes (Horvath, Del Re, Flückiger, & Symonds, 2011).

Acceptance, acceptance, and adoption are frequently used interchangeably, referring to users' willingness to use a system, fully utilise innovation as the best available course of action, and incorporate it into their daily routine when it becomes accessible to them (E. M. Rogers, 2010). However, despite the rapid increase in e-SUD treatments, overall usage rates remain low (Haiden A. Huskamp, 2018; Michelle M. Ng, Joseph Firth, Mia Minen, & John Torous, 2019). Therefore, further research is critical to clarify why some clinicians do not feel comfortable

delivering e-intervention. Nevertheless, adopting ICT for SUD would empower AOD workers to implement evidence-based, more efficient, scalable programs.

Overall, four key issues need to be considered in the substance treatment system, as shown in Figure 7.

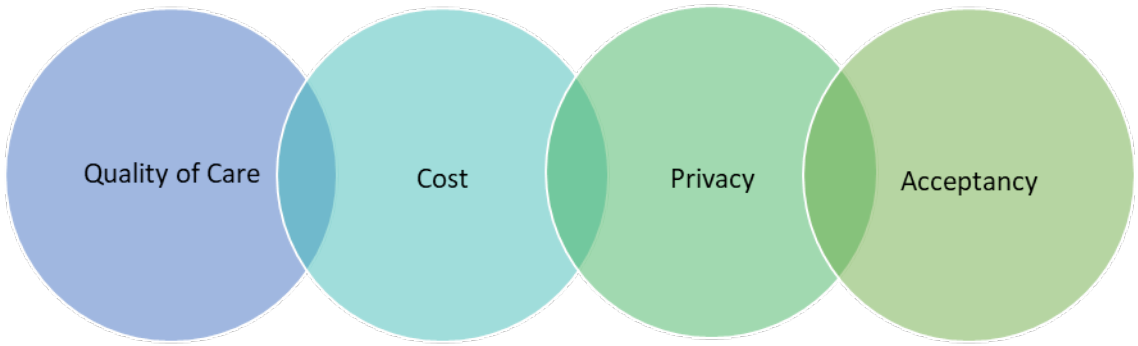

Figure 7 The Four Main Concerns of Applying Digital Health for SUD Treatment.

2.3.4 Critical Perspective of Digital Health in SUDs

E-health-based interventions require multi-context and multi-component strategies and approaches. To maximise the benefits of digital health, it is crucial to consider and address needs across various settings. This includes considering the potential legal repercussions of substance dependency, cultural differences, societal perceptions of substance dependency, and the role of support systems. For instance, clients in the USA expressed high value in a smartphone application designed for heroin recovery (S-Health) due to its potential to address logistical barriers. They saw it as a tool that could help them overcome obstacles related to access and availability. Conversely, clients in China and Taiwan emphasised the application's potential to supplement the limited services currently available to them. They viewed it as a

valuable resource that could enhance their current treatment options (Liang, Wang, & Yuan, 2018; Schulte et al., 2016).

In pursuing effective and sustainable recovery, digital health should integrate various multifaceted strategies, combining knowledge and information, practical and personal skills, and medical and allied support. For example, findings confirmed that texts or phone calls might not increase substance abstinence rates. However, text messaging and practical counselling may be effective alternatives (Vidrine et al., 2019). Kim (2016) supports this multi-pronged approach by demonstrating the enhanced efficacy of technology-based behavioural therapy when added to standard treatment protocols. This research underlines that such augmented strategies could yield better outcomes than medication alone, even amongst those with a history of repeated treatment periods (S. J. Kim, Marsch, Acosta, Guarino, & Aponte-Melendez, 2016). Hence, the research underscores the importance of integrating technology and behavioural intervention into conventional therapy methods to optimise recovery outcomes.

The selection of digital health tools should be suited to the client's characteristics, such as age, gender, and severity of substance dependency. For instance, the BAI program "What Do You Drink (WDYD)" was ineffective for heavy drinking clients aged 15–20 with low education (Voogt, Poelen, Kleinjan, Lemmers, & Engels, 2013). Nevertheless, its efficacy may differ in other demographic groups.

A study indicated a preference for text reminders over phone calls for confidentiality and convenience (Brown et al., 2020). Therefore, further research should consider demographics, intervention duration, and dependency severity to optimise digital health interventions.

The compatibility of digital health tools with client-specific attributes such as age, gender, and severity of substance dependency is a critical factor to consider. For example, the web-based Brief Alcohol Intervention (BAI) program "What Do You Drink (WDYD)" did not prove effective in mitigating alcohol consumption among heavy drinking clients aged 15–20 with low educational

background (Voogt et al., 2013). Nonetheless, its effectiveness may vary with different age or education-based sample groups, underscoring the importance of contextual relevance.

In another study, HIV-infected cocaine users' clients preferred text reminders over phone calls, citing confidentiality and convenience (Brown, Krishnan, Ranjit, Marcus, & Altice, 2020). Therefore, further research should consider demographics, intervention duration, and dependency severity to optimise digital health interventions.

2.3.5 Limitations

This review, though yielding significant findings, carries some limitations. The foremost is the scant data available for analysis. Despite a surge in studies exploring digital health for substance use disorders (SUDs), few assess the use of technological tools in secondary and tertiary interventions, particularly regarding clinician-level technology acceptance challenges.

Comparative analysis of studies presented difficulties owing to a broad spectrum of substances, technological tools, strategies, and methodological variances. Lastly, interventions involving Artificial Intelligence, Virtual Therapeutic Software, Gaming, and social media were excluded due to their broad scope, which is beyond the purview of this review.

2.3.6 Summary

SUD is a chronic and treatable health condition with a high possibility of relapse that requires complex and multi-disciplinary treatment mechanisms. Therefore, it has become increasingly essential to develop electronically based approaches that consider affordable, accessible, multiple contexts, and multi-component strategies. In addition, considering clinician-level barriers to digital health acceptance is vital. Therefore, it is crucial to investigate why some clinicians remain uncomfortable delivering e-interventions and services. Their opinions, engagement, and skills play a significant role in achieving positive outcomes, underlining the need for further exploration in this area.

Table 2 Summary of the Main Findings of the Literature Review

Effectiveness of Digital Health
- Digital intervention for SUDs is effective, but study design, clients' characteristics, and length. Of follow-up, cultural issues should be considered. - Lack of clarity on what type of ICTs are the most effective for a specific group of clients. - Lack of clarity on sustainable effectiveness. - The existing system of care is essential.
Advantages of Digital Health
- Expand the availability of SUD treatments. - Improve privacy. - Provide information with a high degree of standardisation and in real-time. - It might be cost-effective. - They are Flexible and portable for use in different settings. - Are available 24-7.
Challenges of Digital Health
- It may not be appropriate for all clients. - May bias against people with low literacy/e-literacy. - It may expose people to the risk of substance use. - It may be inappropriate in a crisis. - This may cause a lack of face-to-face interaction and virtual intimacy.

2.4 How can digital tools help?

Substance treatment intends to help clients stop or control their compulsive substance-seeking behaviours and use. Various evidence-based treatment methods exist, varying in settings (in-patient or out-patient), forms (medication-assisted or behavioural therapy), and durations.

Treatment for many clients is a lifelong journey involving multiple intervention modalities and ongoing monitoring. No one-size-fits-all treatment exists; the appropriate approach depends on numerous factors, including the client's needs, substance consumed, and financial status. Typically, short-term or singular interventions prove insufficient. Despite progress in medication-assisted treatment (e.g., methadone, buprenorphine, naltrexone), behavioural therapy remains a crucial component of the treatment toolkit (Almutairi, 2021).

Well-established behavioural therapies such as Mindfulness-based Relapse Prevention, cognitive behavioural therapy (CBT), contingency management (CM), Motivational Interviewing (MI), and Brief Alcohol Intervention (BAI) have continued to demonstrate effectiveness in reducing substance dependency for different target groups(Barrowclough et al., 2014)

Previous studies (Berry, Bucci, & Lobban, 2017) have highlighted the potential of digital tools to enhance social inclusivity, particularly for groups that are difficult to reach, such as those with mental health challenges and substance dependency.

Despite recent advancements in digital inclusion there are still individuals who remain digitally excluded. Although digital solutions hold promise for bridging healthcare gaps and enhancing service scalability, it is crucial that they foster inclusivity rather than exacerbate the social inequalities prevalent among those experiencing SUD (Robotham, Satkunanathan, Doughty, & Wykes, 2016).

One perceived advantage of digital systems is their potential to enhance the sense of empowerment, control, and choice within healthcare pathways, areas where traditional doctor-led and clinician-led care have historically fallen short. Another perceived benefit is data ownership, which allows service users to decide whether or not they wish to share their digital data. Furthermore, digital technology, with its instant and widespread access to information, as well as both intentional and unintentional digital authorship, has transformed how we interact with services (Bucci, Schwannauer, & Berry, 2019). This shift challenges associated with the traditional treatment approaches of data ownership and introduces several ethical dilemmas that must be carefully addressed when integrating digital systems into healthcare services

Therefore, it is imperative to make additional efforts to assess the quality of these tools, either by guaranteeing that people experiencing SUD have access to evidence-based and evidence-informed digital tools or by equipping them and the AOD clinicians with the skills needed to make informed decisions regarding their potential effectiveness.

Individuals with substance use disorders (SUD) often face a complex array of co-occurring psychosocial and social challenges, including homelessness or unstable housing, strained social networks, involvement with the criminal justice system, experiences of violence, stigma, shame, abuse, trauma histories, and mental health issues. Digital solutions have been developed to enhance the efficiency and cost-effectiveness of social welfare and healthcare in addiction treatment. Given the diverse severity of issues related to alcohol and drug use, these digital tools have the potential to reduce costs while offering personalized, tailored care (Kosonen, Shorter, & Kuusisto, 2024). So, many aspects of these tools need to be explored and examined across different populations, settings, and stages of their treatment journey.

For AOD workers, digitalization also represented a significant shift, necessitating the re-learning of familiar work processes and increasing cognitive burden under already stressful conditions. As with advances in AI for health and social care, it will be crucial to monitor these tools for accuracy and quality of care (Rehm et al., 2013). Given the varying severity of issues related to alcohol and drug use, digital service tools can reduce costs and provide more tailored care compared to the limited face-to-face services available. This thesis will delve deeper into these possibilities.

2.4.1 Digital Tools as A Medium of Behavioural Treatment Delivery

Digital health tools, designed to induce behavioural and cognitive changes, employ various methods—from plain text reminders to advanced wearable biomedical sensors and GPS-enabled smartphones. They can be integrated into the SUD treatment process through three primary ways: (1) as additional components to enhance standard care, (2) as partial substitutes for standard care, or (3) as complete replacements for standard care (Rosa, Campbell, Miele, Brunner, & Winstanley, 2015). However, the constructive collaboration between SUD treatment and digital technology can differ across settings or client groups.

2.4.2 How Clinicians Use Digital Health Technology in Practice?

Depending on the primary target consumer—whether it be clients, clinicians/service providers, health system or resource managers, researchers, or data services—e-tools can offer direct or indirect support for a broad spectrum of activities. Therefore, the target group of this study—clinicians, Alcohol and Other Drugs (AOD) workers, counsellors, social workers, addiction counsellors and other practitioners—can leverage digital health in numerous ways, as illustrated in Table 3. For instance, this utilisation can foster opportunities to engage clients, integrate real-time data into therapy planning, avert relapses, and advocate for evidence-based treatment approaches. In addition, the platforms, tools, strategies, and networks represented in Table 3 can benefit current clients and those who have completed the treatment process and are recovering. For example, research indicates that prolonged clinical engagement correlates with improved SUD outcomes. In addition, aftercare facilities, robust support networks, transition assistance, and extended discharge periods are crucial facilitators for long-term rehabilitation and recovery (Manuel et al., 2017).

To this end, integrating most, if not all, evidence-based SUD treatment approaches with digital-enabled processes could significantly enhance the efficiency of substance treatment.

Table 3 Classification of Possible Digital Health Interventions for AOD Practitioners

Categories		Example of Intervention
1	Client Identification & Registration	1. Verify client's unique identity 2. Enroll client for health services/clinical care plan
2	Client's Health Records	1. Tracking of clients' health status and services 2. Manage client's structured clinical records 3. Manage client's unstructured clinical records 4. Routine health indicator data collection and management
3	Decision Support	1. Provide prompts and alerts based according to protocol 2. Provide checklist according to protocol 3. Screen clients by risk or another health status
4	Telemedicine	1. Consultations between remote client and AOD workers 2. Remote monitoring of client health or diagnostic data by AOD workers. 3. Transmission of medical data to health care provider. 4. Consultations for case management between health care provider(s)
5	Communication	1. Communication from an AOD worker(s) to supervisor. 2. Communication and performance feedback to AOD worker(s) 3. Transmit routine news and workflow notifications to AOD worker(s) 4. Transmit non-routine health event alerts to AOD worker(s) 5. Peer group for AOD workers
6	Referral	1. Coordinate emergency response and transport 2. Manage referrals between points of service within the health sector 3. Manage referrals between health and other sectors
7	Assessments	1. Identify client(s) in need of services 2. Schedule AOD workers' activities
8	Training	1. Provide training content to an AOD worker(s) 2. Assess the capacity of AOD worker(s)
9	Medication Management	1. Track client's medication consumption 2. Report overdose or other events
Adopted from Classification of digital health interventions. Geneva: World Health Organization; 2018(WHO/RHR/18.06).		

2.5 Why are clinicians important?

Implementing digital health technology in SUD treatment necessitates incorporating it into clinical workflows. Notably, the most substantial obstacle to implementing e-health technologies is often their initial adoption by health providers. Therefore, overcoming these implementation challenges is crucial before the focus can shift to clients' adoption or sustained usage (Fleddermann et al., 2021).

While AOD workers play a vital role, their voice is often absent in discussions surrounding digital health intervention in SUD. Further, when technological interventions are employed, they are usually done without involvement from clinicians or providers (Brown et al., 2020). This suggests that clinicians need more inclusive decision-making processes when adopting digital health interventions.

By exploring the acceptance of digital health by AOD workers in Australia, this research aims to address the empirical gap and delve into the following critical issues in detail: Address substance harm and treatment challenges.

- Address Substance Harm and Treatment Challenges in Australia
- Formulating digital health policies and their integration with SUD treatment.
- Establishing a sustainable synthesis between digital health and everyday clinical

2.5.1 To Address Substance Harm and Treatment Challenges in Australia

Alcohol and other drug (AOD) use in Australia has substantial health, social, and economic effects. As per the 2019 National Drug Strategy Household Survey, between 2018 and 2019, approximately 16.4% of the population used an illicit substance, an increase from 2007's 13.4%. The most common substances used in 2019 were cannabis (11.6%), cocaine (4.2%), and ecstasy (3.0%) (AIHW, 2022b).

The economic repercussions of licit and illicit drug misuse in Australia are considerable. Estimates highlight staggering costs associated with tobacco ($136.9 billion in 2015–16), opioids ($15.76 billion in 2015–16), methamphetamine (over $5 billion in 2013–14), and alcohol ($14.35 billion in 2010), emphasising the severity of the issue (Manning, Smith, & Mazerolle, 2013; S Whetton et al., 2016; Steve Whetton et al., 2021). In addressing these challenges, clinicians must leverage their empirical knowledge and understanding of case-specific factors tied to substance harm (Allnutt et al., 2013). This expertise is instrumental in developing appropriate interventions to mitigate the identified risks.

SUDs Treatment Availability in Australia

Australia provides a range of treatment interventions, mostly covered by Medicare (free public health system), to assist individuals in pursuing substance-free lifestyles. In 2021-2022, 228,451 treatment episodes were provided for substance misuse, averaging 1.8 episodes per client. Although this reflects a 41% increase since 2012-13, it is a 6% decrease from the previous year.

AOD practitioners and other clinicians predominantly provided counselling, accounting for 36% of all treatment episodes. This was followed by assessment only at 21% and Support and Case Management at 15%. Among clients seeking support for their substance misuse, counselling was the primary treatment for 37%, while 22% received assessment only (AIHW, 2023).

AOD Workforce Status in Australia

In Australia, many professionals, including health and non-health professionals, interact with individuals facing substance use problems. As per the National Survey Results of Australia's AOD Workforce, 2019-2020, the most prevalent occupations dealing with AOD issues were drug

and alcohol counsellors (23%), nurses (10%), and social workers (8%), often working in non-governmental organisations shown in Figure 8.

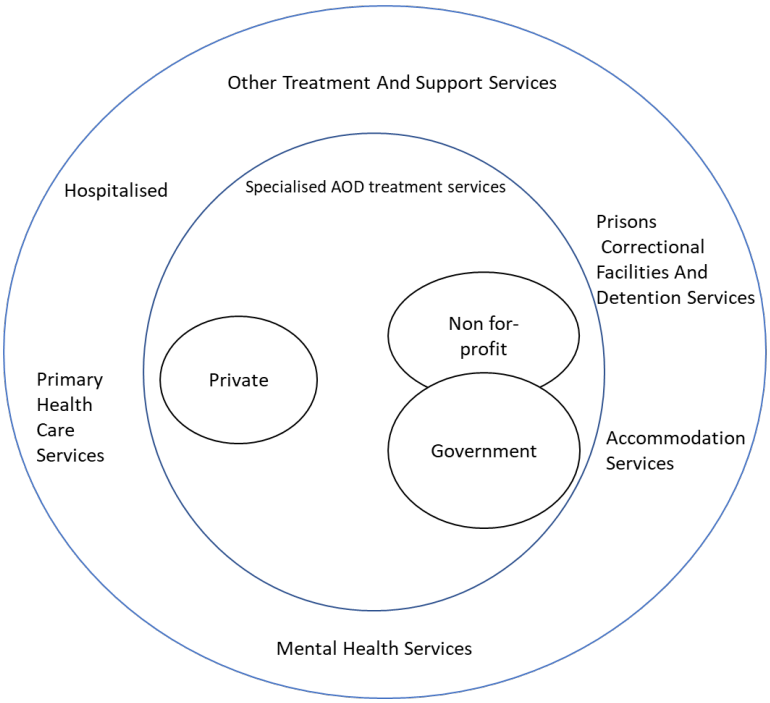

Figure 8 Categories of 1282 Treatment Services in Australia

The report indicated significant growth in the number of AOD treatment providers over the past decade, with increases seen across Victoria (from 138 to 404), New South Wales (from 258 to 440), Queensland (from 118 to 180), and Western Australia (from 52 to 108). The majority of these providers (69%) were NGOs, and a significant proportion (59%) were situated in major cities(Skinner, McEntee, & Roche, 2020b). The majority of the AOD workforce was female (69%) and aged over 36 (76%), mirroring trends seen in human services fields globally. Notably, a considerable proportion (65%) of AOD workers reported lived experience with substance use, either personally or via family or friends. Most of these professionals held an undergraduate or higher education (Skinner, McEntee, & Roche, 2020b), as presented in Figure 9. Indeed, the

findings of this research could offer valuable insights for diverse Australian clients striving for sobriety. Additionally, the findings could inform advancements in AOD worker training, enhancing future care delivery in Australia.

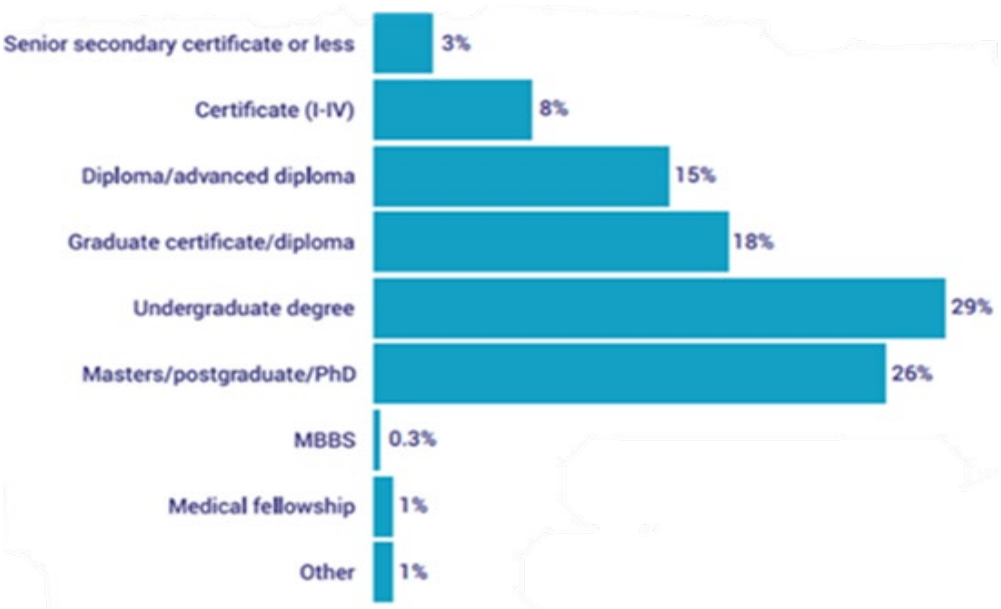

Figure 9 AOD Workers Professional Qualification

2.5.2 To Develop Digital Health and SUD Treatment Policy

Recognising SUD as a chronic brain condition requires innovative and integrated solutions that extend beyond acute treatment. Ensuring that ambiguous standards, regulations, policies, or frameworks do not impede client care enhancement is crucial in our rapidly evolving technological landscape. Consequently, practical, national guidelines and frameworks for government entities and service providers in Australia are paramount.

This study will initially conduct semi-structured interviews with treatment providers and follow up with a survey of AOD clinicians in Australia to explore the ‘lived effects’ in the real world. The research aims to reveal crucial insights into the key determinants influencing the acceptance of treatment providers.

By investigating clinicians ' acceptance and viewpoints, the study can better inform future AOD policymakers, treatment agencies, academicians, and I.T. experts. This knowledge would enable them to devise more integrated treatment approaches. Neglecting to consider digital health acceptance by the existing AOD workforce while developing policies could inadvertently lead to detrimental policy outcomes. This study endeavours to address this gap.

2.5.3 To Establish a Sustainable Integration Between Digital Health and Everyday Practice

Digital health possesses the transformative potential to alter patient-provider interaction, allowing for more prolonged but less intensive treatment episodes. However, several significant issues need addressing to make digital tools more sustainable in clients' care. A primary concern is how AOD workers adapt their daily practices to utilise these e-tools appropriately.

Long-term and pervasive clinician use of digital tools may require more than updating skills and training workshops; indeed, introducing e-tools could alter clinicians' professional roles, such as AOD workers. For example, their responsibilities may shift from direct treatment to a more supportive role that includes offering feedback on e-based modules, creating environments for social skill practice in VR, or aiding clients in gaining insights from data gathered by wearable devices. This evolution can potentially enhance patient care but necessitates redefining clinicians' roles and revisiting their training requirements (B. Meskó, Drobni, Bényei, Gergely, & Győrffy, 2017; Bertalan Meskó, Radó, & Győrffy, 2019).

From the other point of view, digital health is not advanced technology alone but a cultural transformation. The cultural change is "how disruptive technologies that provide digital and objective data accessible to caregivers and patients lead to an equal level doctor-patient relationship with shared decision-making and the democratisation of care" (B. Meskó et al., 2017, p. 26).

Nevertheless, by taking an interdisciplinary approach and applying the extended version of the Technology Acceptance Model customised for the AOD workforce in Australia, this research will explore how sustainable e-integrated care can be achieved and enhanced by better comprehending how clinicians see the clinical effect of digital health and how they accept digital health in practice. Therefore, Clinicians' technology acceptance level can influence clients' care experiences.

2.6 Summary

Digital health supplies an intriguing and hopeful advancement in treating SUD. The fast-paced evolution of digital tools offers exciting potential, yet their sustainable adoption hinges on numerous technical and non-technical factors—including clinician acceptance—which must be appropriately tackled for us to realise their full potential. Therefore, digital health must be integrated into health priorities to aid clients sustainably, securely, and ethically. In addition, principles of transparency, scalability, accessibility, replicability, interoperability, and privacy should underpin their development and operation.

CHAPTER 3: LITERATURE REVIEW- TECHNOLOGY ACCEPTANCE

3.1 Overview

In the scholarly exploration of technology acceptance, various terminologies such as 'acceptability', 'acceptance', and 'adoption' are frequently employed interchangeably, reflecting the complex nature of the field. " Technology acceptance" is a focal point in information systems and IT. Research is typically defined as the propensity of individuals to employ or endorse the use of innovative Information and Communications Technology (ICT) or products. Essentially, it relates to how willing an individual is to embrace new technology (Agarwal & Prasad, 2000; Dillon & Morris, 1996).

Various theoretical models have been applied to explain and foresee user behaviour in diverse contexts. These encompass the Theory of Reasoned Action (TRA) (M. Fishbein, 1979), the Diffusion of Innovation (DOI) (E. M. Rogers, 1962), the Technology Acceptance Model (TAM)(Davis, 1989), the Technology Organisation Environment (TOE) framework (Tornatzky, Fleischer, & Chakrabarti, 1990), the Theory of Planned Behaviour (TPB) (Ajzen, 1991) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003).

This chapter represents the second part of the literature review, focusing on established theoretical models concerning technology acceptance. It aims to critically assess these models' principal strengths, limitations, and applications in previous research endeavours. Subsequently, the most appropriate theory that aligns with this study's research question will be identified and selected. This discussion sets the stage for Section 3.3, where the Conceptual Model is introduced and justified, providing a theoretical basis and rationale for its selection and application in this research.

3.2 Technology Acceptance Theories

3.2.1 Theory of Reasoned Action (TRA)

Originating in the field of social psychology, TRA (Ajzen&Fishbein, 1980; M. Fishbein, 1979) has been applied successfully in a wide variety of disciplines to explain user behaviour (L.-d. Chen, Gillenson, & Sherrell, 2002; Rejali, Aghabayk, Esmaeli, & Shiwakoti, 2023). According to this model, there is a relationship between attitudes, which can be described as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (Eagly & Chaiken, 1993, p. 15) and behaviour. Hence, a person's attitude towards any subject or object can be projected, and behaviours can be examined by their pre-existing attitudes, behavioural intentions, and social influence of subjective norms (Ajzen & Fishbein, 1975a).

The main shortcoming of TRA is that it assumes that individual behaviours are under volitional control, which is not continuously the case. People might not be acting because of a decision or choice. Moreover, it assumes that behaviours result from a straightforward decision-making process and does not consider behavioural change over time. Broadly, there is not always an explainable justification for action (Gotch & Hall 2004).

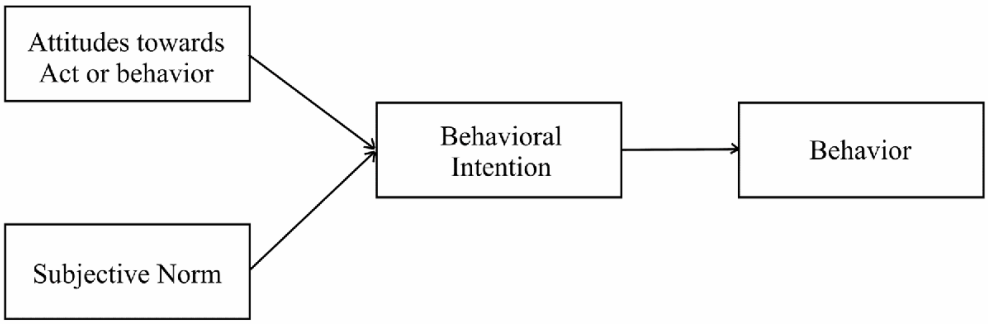

Figure 10 Theory of Reasoned Action (Ajzen & Fishbein, 1975a).

3.2.2 Theory of Planned Behaviour (TPB)

Ajzen (1991) proposed the Theory of Planned Behaviour (TPB), an extension of the Theory of Reasoned Action (TRA), to explain individuals' behaviours in specific circumstances. (TPB) posits that an individual's action is decided by the interaction of three components: attitude, subjective norm, and perceived behavioural control, as illustrated in Figure 11. Perceived behavioural control consists of two aspects:

1- Control beliefs are the resources needed to execute a behaviour.
2- Perceived facilitation is the resource that could expedite an individual's performance (Ajzen, 1991).

TPB is a dominant theory for explaining and forecasting behaviour, notably in situations where individuals lack control over their actions, often due to the absence of the right resources and opportunities (McEachan, Conner, Taylor, & Lawton, 2011). Like most acceptance theories, TBP evolved, and Taylor and Todd's new model was called the Decomposed Theory of Planned Behaviour (S. Taylor & P. Todd, 1995). Many studies in various domains have proved the TPB theory to be a respected framework for rationalising and predicting the acceptance of new digital health technology (Sadoughi, Khodaveisi, & Ahmadi, 2019).

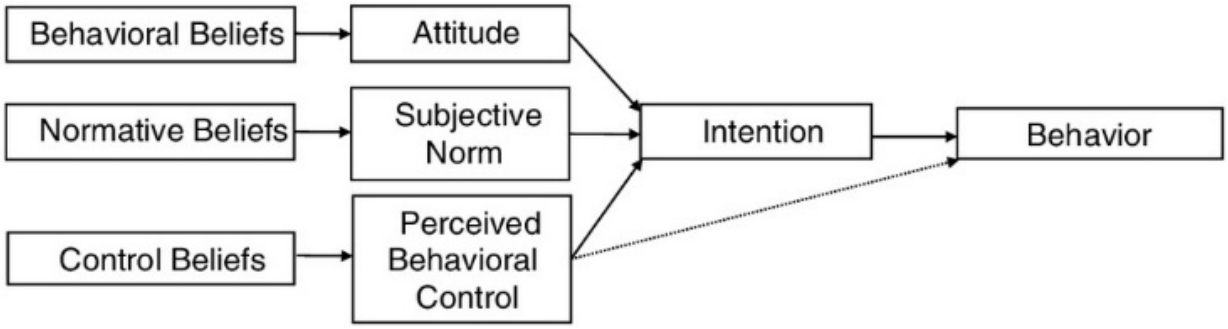

Figure 11 Theory of Planned Behaviour (Ajzen, 1991)

The central presumption of TPB is that individuals make rational selections based on the available information. However, a key critique is its emphasis on rational thought, neglecting unconscious influences on behaviour and the impact of emotions on expected outcomes. Additionally, its static analytic nature limits its utility in predicting future behaviours and their consequences (Sniehotta, Presseau, & Araújo-Soares, 2014). Thus, the components of these theories are not clearly demarcated. Thus, applying this theory in SUDs and digital health settings with many variants and multi-level natures is challenging. Attitudes toward the behaviour and subjective norms are insufficient to fully account for the clinician's digital health use intention in this research.

3.2.3 Decomposed Theory of Planned Behaviour (DTPB)

The Decomposed Theory of Planned Behaviour (DTPB), introduced by Taylor and Todd in 1995, offers distinct advantages over other models by identifying specific salient beliefs that may influence information technology usage. This model is particularly noted for its superior predictive power compared to the traditional Theory of Planned Behaviour (TPB) and the Technology Acceptance Model (TAM). Taylor and Todd emphasize the added value of their model, stating, In comparing the two versions of TPB, the study believe that there is value added as a result of the decomposition, in terms of increased explanatory power and a better, more precise, understanding of the antecedents of behaviour. While they acknowledge that TAM might be preferable if the sole objective is to predict usage, they argue that the decomposed TPB offers a more comprehensive understanding of usage behaviour and intentions. This, in turn, may provide IT managers and researchers with more effective guidance for system implementation (S. Taylor & P. A. Todd, 1995).

In details, in (DTPB), attitudinal, normative, and control beliefs are further refined into specific constructs derived from the literature, particularly incorporating elements from the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) theory. The attitudinal belief structure is decomposed into constructs such as "perceived usefulness," "perceived ease of

use," and "compatibility." Researchers suggest that normative beliefs can be broken down into relevant reference groups, such as peers, superiors, and subordinates, each potentially holding differing perspectives on the use of digital technology. Taylor and Todd (1995) specifically used peers and superiors to represent this decomposition of normative belief structures.

Control beliefs in the DTPB are decomposed into two key constructs: self-efficacy and facilitating conditions. Self-efficacy pertains to an individual's perceived ability to use a new technology effectively. Facilitating conditions, on the other hand, encompass two dimensions of control beliefs: one related to resource factors, such as time and money, and the other focusing on technology compatibility issues that might hinder usage (Ajzen, 1991).

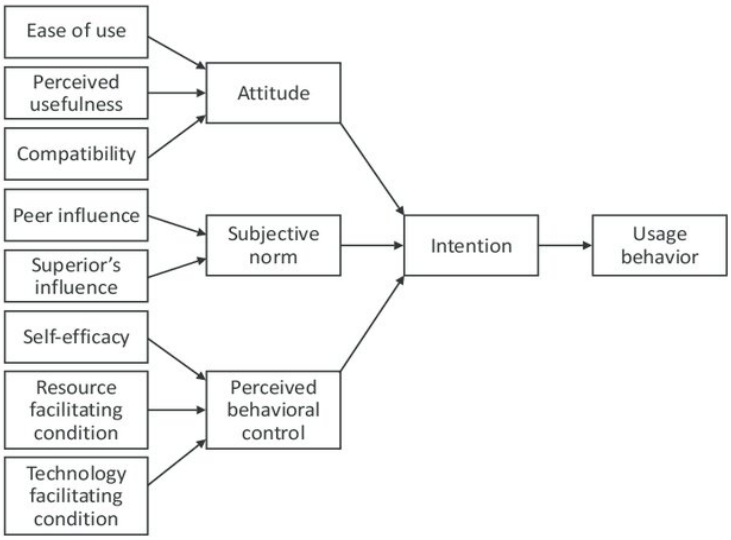

Figure 12 The Decomposed Theory of Planned Behaviour. Taylor & Todd, 1995

3.2.4 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), initially introduced by Fred F.D. Davis in 1985 (Davis, 1985), has continuously evolved (Legris, Ingham, & Collerette, 2003) to become one of the most influential models in the Technology Acceptance (TA) field. It supplies an information system framework that explains how customers adopt and utilise technology. TAM differs from the Theory of Reasoned Action (TRA) in two main aspects (see Figure 13): perceived usefulness

(PU), which measures an individual's belief in the ability of a specific information and communication technology (ICT) to enhance their job performance, and perceived ease of use (PEU), which assesses an individual's perception of the simplicity of employing a particular ICT.

In the TAM, behavioural intention is defined as "the strength of one's intention to perform a specified behaviour" (Martin Fishbein & Ajzen, 1975, p. 216). Unlike other models, TAM does not incorporate subjective norms as determinants of user acceptance but instead focuses on the influence of attitudes towards ICT, as attitudes directly affect the intentions to use technology. Attitude plays a crucial role since some customers may still adopt and utilise e-tools despite harboring a pessimistic attitude due to workplace requirements. Therefore, it is also critical to assess the satisfaction level of end-users to obtain a comprehensive understanding of the acceptance and usage of technology.

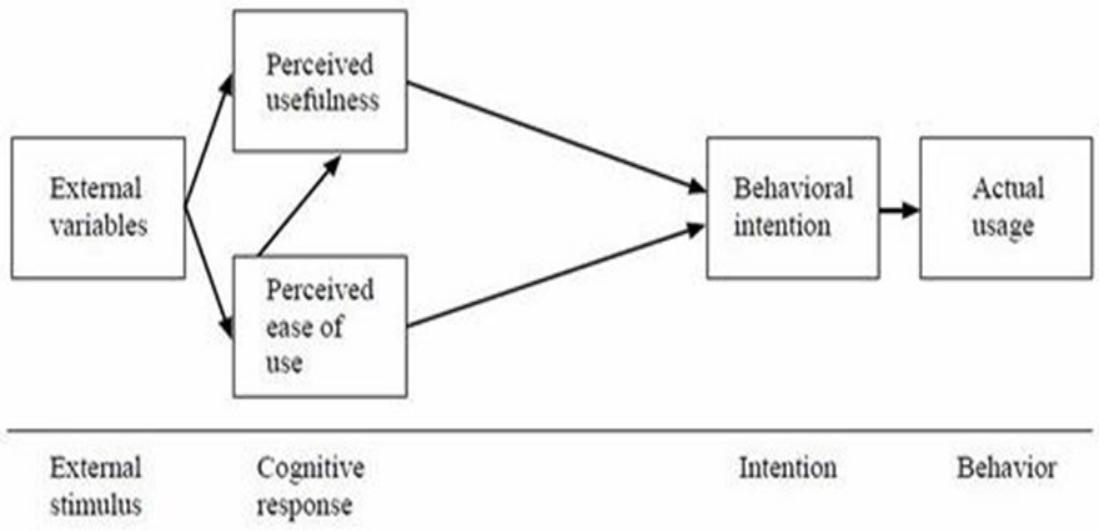

Figure 13 Technology Acceptance Model (Davis, 1985)

Since the TAM emphasises behavioural intention and cognitive beliefs only, it has been criticised for ignoring social and human elements that may affect the prediction of digital health use (Taherdoost, 2018). This concern has given rise to TAM's extended styles, such as the TAM

2 by Venkatesh and Davis, that integrated other factors such as experience, career relevance, image and voluntary processes with cognitive processes (Venkatesh & Davis, 2000).

Overall, TAM remains a practical and straightforward theoretical model that has been extensively cited in numerous published papers. It is commonly employed to examine the level of technology acceptance among diverse customers and is considered the most successful model for assessing ICT acceptance worldwide. Simultaneously, researchers have added elements from other models and integrated them into their field of study (Rahimi, Nadri, Afshar, & Timpka, 2018). Thus, it cannot be suitable for all studies; adjustments may be necessary depending on the subject, sample and study model.

3.2.5 Diffusion of Innovation Theory (DOI)

The Diffusion of Innovations (DOI) theory aims to explain how, why, and at what rate innovative ideas and technologies spread. Diffusion refers to the process through which innovations are communicated over time via specific channels among participants in a social system, and diffusion is a social process among individuals or organisations in response to learning about new or extended digital health innovation. This theory has been widely applied in various fields and proposes that four factors influence the process of diffusion:

1- Innovation refers to a venture, object, or idea that individuals or adoption units perceive as new.
2- Time: Is needed for innovations to be accepted
3- Communication Channels: These are the tools through which communications about innovation are transferred from one person to another.
4- Social Systems: This includes external factors like media, infrastructure, and organisational requirements, as well as internal factors such as proximity to leadership and the strength of social connections.

The collective influence of these roles within a social system determines the likelihood of adoption by potential adopters (J. Kaminski, 2011; E. M. Rogers, 1983). The DOI theory suggests an S-shaped curve of innovation, where the adoption begins to increase after opinion leaders start embracing the new concept. According to the acceptance stages illustrated in

Figure 14, adopters can be classified into innovators, early adopters, early majority, late majority, and laggards.

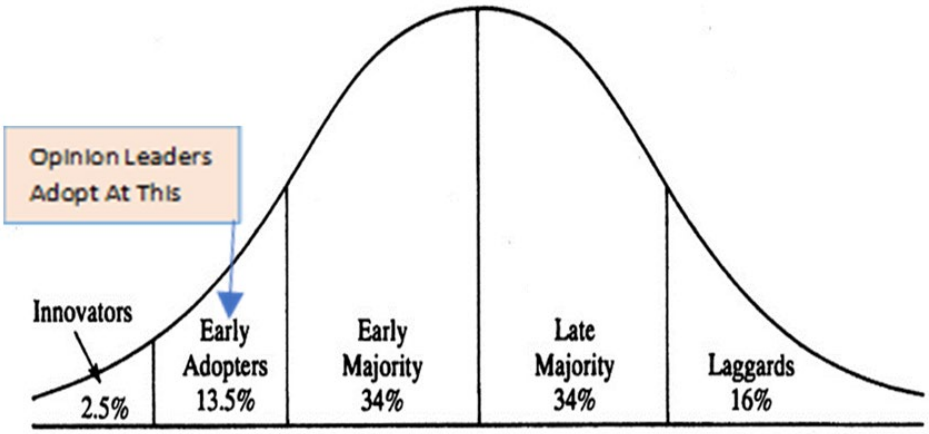

Figure 14 Diffusion of Innovations Adopter Categories (E. M. Rogers, 1983)

The DOI theory has undergone extensions, leading to the development of the Refined DOI (RDOI) model, which shifts the focus from innovation to the perceived characteristics of its application. This refined model, proposed by Moore and Benbasat in 1991, redefines the concepts of DOI to Centre around the utilisation of innovation (G. C. Moore & Benbasat, 1991). The RDOI theory puts forth seven concepts that impact the adoption of digital health, as depicted in Figure 15.

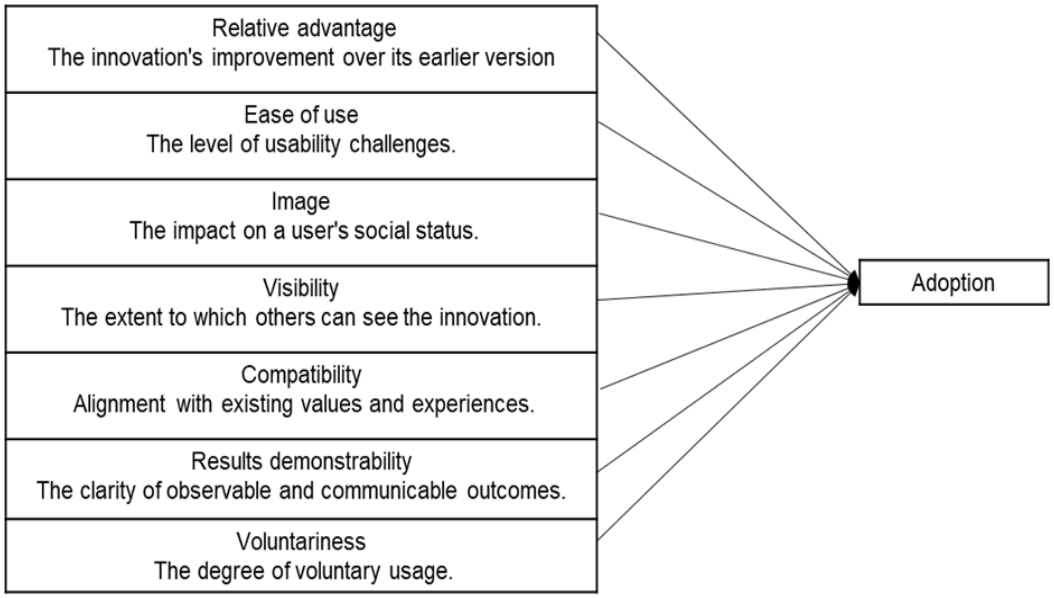

Figure 15 Refined DOI (Moore & Benbasat, 1991)

Scholars have varying views on the robustness of TAM, with some favouring DOI for its broader explanatory scope. Additionally, some researchers argue that TPB offers advantages over TAM by incorporating social influence and control factors not found in other theories. Finally, it is worth noting that DOI's relative advantages and complexity components align with TAM's PU and PEU, suggesting that TAM can be considered a subset of DOI (Taherdoost, 2018).

DOI theory is valuable in finding the acceptance rate of ICT; however, it falls short in explaining how technology progresses into acceptance or rejection. Additionally, quantifying DOI is challenging due to the complexity of human networks and interactions. As a result, it becomes difficult, if not impossible, to precisely measure the factors that trigger innovation acceptance (Damanpour, 1996). In complex settings, such as digital health in SUDs treatment settings, where clients and clinicians receive information from various sources and are influenced by internal and external stimuli, such as family, government policies, and treatment availability, a one-way model is insufficient to capture the intricacies involved.

3.2.6 Technology-Organisation-Environment (TOE)

The Technology Organization Environment (TOE) framework offers an organisational-level perspective on technology adoption, focusing on technological, organisational, and environmental contexts rather than individual behaviours. Tornatzky and Fleischer (1990) defined these contexts:

- Technological context refers to ICT tools that are internally and externally available to an Organisation.
- Organisational context relates to features such as organisation size, structure, leadership, complexity, and the quality and quantity of human and slack resources.
- Environmental context encompasses government policies and competitor actions. Collectively, these factors influence an organization's acceptance and integration of technology (Tornatzky, Fleischer, & Chakrabarti, 1990).

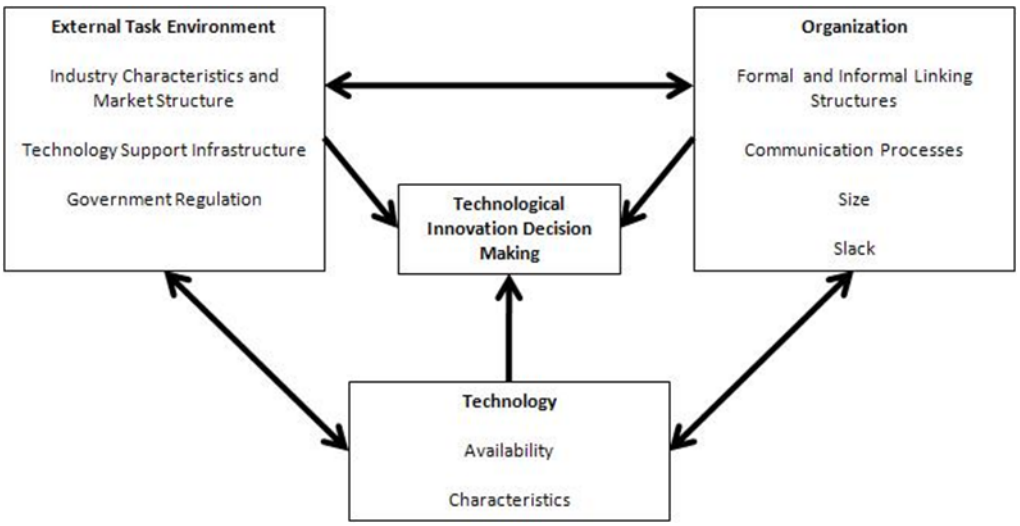

Figure 16 Technology-Organisation-Environment (Tornatzky, Fleischer, & Chakrabarti, 1990)

Despite its extensive use, the TOE theory has seen limited theoretical advancement since its start. This can be attributed to its "generic" nature, allowing a wide range of factors with minimal need for changes to the theory itself (Zhu & Kraemer, 2005). Another issue Baker (2012) pointed out is that the theory aligns "too well" with other technology acceptance models and does not provide unique insights, leaving little impetus to modify TOE (Baker, 2012). Given that this model centers on the organisation rather than the individual clinician, it may not be the most suitable for this study.

3.2.7 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), explained by Venkatesh et al. (2003), aims to elucidate users' intentions to use ICT and later usage behaviour. This theory synthesises a more inclusive understanding of the acceptance procedure than earlier models.

Eight existing ICT adoption theories were amalgamated into the UTAUT model, including (1) the Theory of Reasoned Action (TRA); (2) the Technology Acceptance Model (TAM); (3) Theory of Planned Behavior (TPB); (4) Combined TAM-TPB; (5) Model of PC Utilisation (MPCU); (6) Motivational Model (MM); (7) Social Cognitive Theory (SCT); and (8) Innovation Diffusion Theory (IDT). This integrated model was formed and based on the theoretical and empirical likenesses among these eight models (Venkatesh et al., 2003).

The UTAUT theory, represented in Figure 16, is built around four central constructs:

1- Performance Expectancy (PE): This is the extent to which an individual think using the system will help extend improvements in job performance.

2- Effort Expectancy (EE): This is the degree of ease related to using the system.

3- Social Influence (SI): This is the extent to which an individual perceives that significant others believe they should source the new system.

4- Facilitating Conditions (FC): This is the degree to which an individual believes that an organisational and technical infrastructure occurs to support the system's use.

The first three directly influence consumer intention and behaviour, while the fourth directly affects consumer behavior alone. Factors such as gender, experience, age, and voluntary use are proposed as mediators of these constructs. The UTAUT model is presented in Figure 17 and the relationship between the TAM and UTAUT is shown in Figure 18.

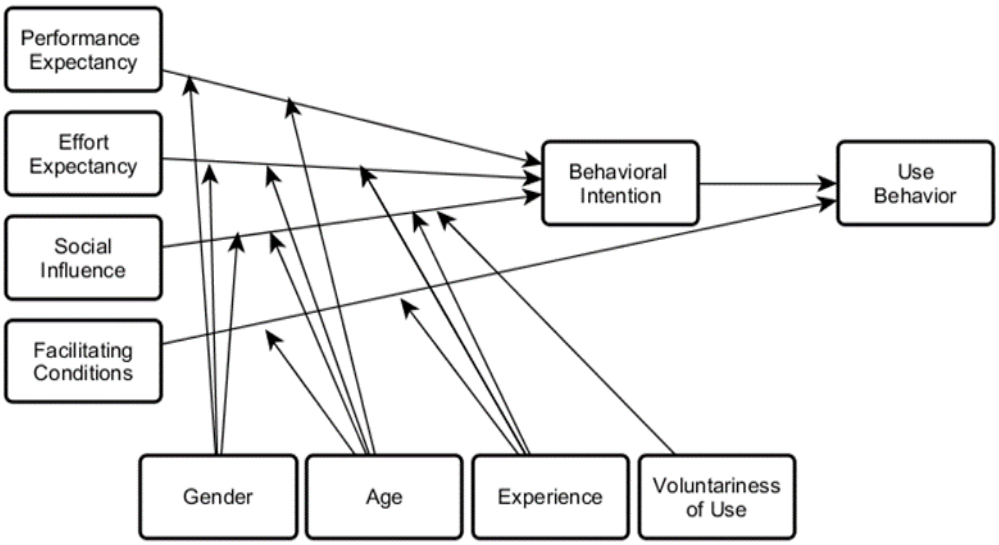

Figure 17 Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003)

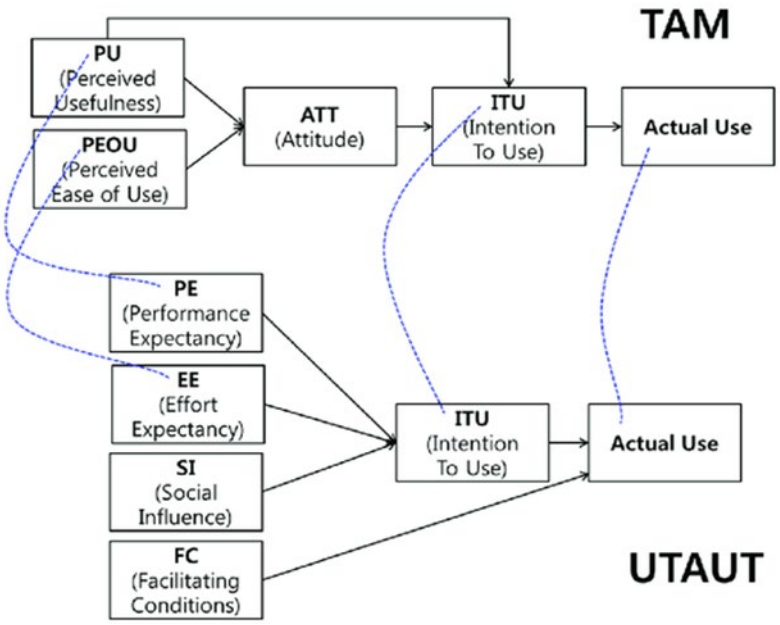

Figure 18 Comparison of the TAM and UTAUT Models (S. Kim, Lee, Hwang, & Yoo, 2016)

3.2.8 The Advantages of the UTAUT Model and Justification for Using this Model.

UTAUT has been universally applied and evaluated in various contexts to predict the adoption and integration of electronic tools. This includes areas such as near-field communication technology (Khalilzadeh, Ozturk, & Bilgihan, 2017), the use of interactive whiteboards (Šumak, Pušnik, Heričko, & Šorgo, 2017), mobile health (m-health) applications (Hoque & Sorwar, 2017), home telehealth systems (Cimperman, Makovec Brenčič, & Trkman, 2016), and many more. Specifically in the field of digital health, the UTAUT model has been adapted and utilised to examine the adoption of digital health interventions by patients (Ebert et al., 2015; Hennemann, Beutel, & Zwerenz, 2016) and healthcare professionals (Gu et al., 2021; Hennemann, Beutel, & Zwerenz, 2016).

The UTAUT model supplies a theoretical framework that describes ICT acceptance and illuminates the actual usage of such innovations. This model can account for about 70% of the variance in behavioural intention and roughly 50% of the variation in the actual use of ICT

(Venkatesh et al., 2003). The model's broad application and replication, either in whole or in part, in various organisational settings have reinforced its generalisbility. Therefore, this study will utilise the UTAUT model as its theoretical core for assessing the acceptance of technology by AOD workers in Australia.

Several researchers have highlighted the need to enhance UTAUT's predictive ability for ICT acceptance by including other external variables such as self-efficacy, habits, trust, satisfaction, and perceived risk. Including these variables aims to capture the unique dimensions of technology acceptance and the influence of external factors on it (Lee et al., 2003). For instance, some researchers incorporated personal innovation specificity and trust to assess behavioural intentions for M-learning while integrating integrated self-efficacy, risk, trust, security, and attitude to evaluate behavioural intentions for mobile payments. These efforts to expand the UTAUT model show the recognition of the importance of incorporating added variables to improve the understanding of technology acceptance (Kabra, Ramesh, Akhtar, & Dash, 2017).

To our knowledge, the UTAUT model has not been previously used to study the acceptance of digital health among Alcohol and Other Drugs (AOD) workers in Australia. Therefore, contextualisation is necessary in this specific setting. Earlier researchers have suggested using belief elicitation as the preferred method to contextualise behaviour theories in new populations (AOD clinicians) and new behaviours of interest (applying digital health in substance use disorders treatment settings), particularly in the context of the COVID-19 era.

This research aims to uncover the beliefs of AOD workers by examining their responses to questions related to the positive and negative influences of UTAUT constructs. These beliefs will not only supply contextualisation for the UTAUT model in the context of digital health in substance use disorders but also address a theoretical gap and contribute to the extension of the UTAUT model. Therefore, this study aims to integrate key factors from the substance use disorders literature to predict technology acceptance and Utilisation by AOD clinicians.

3.3 Co- Design

Research indicates that, in addition to the various factors identified in the preceding theories that affect technology acceptance, a lack of understanding of end-user preferences can also contribute to the failure of new technologies. Co-design, an approach rooted in human-centered design principles, involves collaboration between professional designers and non-designers throughout the design development process (Sanders & Stappers, 2008). This participatory method is gaining traction as it democratizes the design process, allowing diverse stakeholders to share their perspectives in open, public spaces rather than being constrained by hierarchical, institutional boundaries (Björgvinsson, Ehn, & Hillgren, 2010).

Co-design is an intervention design approach that gives equal weight to both academic knowledge and lived or living experience. It focuses on co-creating with individuals who have firsthand experience and other key stakeholders, such as clinicians, policymakers, managers, and leaders. This approach is particularly beneficial for marginalized and vulnerable populations, like, SUD as it can help reduce barriers to participation, such as perceived power imbalances, stigma, and fear of judgment. By fostering active collaboration during the development process, co-design enhances alignment between the end user/clinicians, the digital intervention, and the specific context, leading to improved uptake, adoption, and engagement (D'Arcey et al., 2024).

While co-design offers benefits to clients, it also involves costs, particularly the time required for participation. Consumers with more available time are more likely to engage in co-design, and specific skill sets can further influence their willingness to participate. Additionally, co-design is not equally effective for all products; it is most appealing for goods and services that offer greater opportunities for customization, as these products align more naturally with the co-production process (Etgar, 2008).

In conclusion, co-design is a valuable approach that combines academic and lived experience to create more inclusive and effective interventions. It is particularly beneficial for

marginalized populations by reducing barriers like stigma and power imbalances, though it also involves costs such as time and specific skills. While its effectiveness may vary depending on the type of product or service, co-design ultimately fosters greater relevance, uptake, and engagement in digital interventions.

So, this study will seek clinicians' opinions on various aspects of their interaction with technology in their daily work and direct engagement with clients. It aims to explore how digital interventions may help bridge certain gaps, with co-design playing a crucial role in clinicians technology acceptance.

3.4 Task-Technology Fit

The Task-Technology Fit (TTF) model, proposed by Goodhue and Thompson (1995), suggests that effective technology use and improved individual performance depend on how well the technology aligns with the specific requirements of a task. The model was designed to fill a gap in understanding the relationship between technology adoption and performance in both public and private sectors, particularly in the post-adoption phase of technology use. Prior research had primarily focused on factors such as attitudes, beliefs, and intentions toward technology use, without sufficiently exploring the impact of technology on performance outcomes (Goodhue & Thompson, 1995).

The Task-Technology Fit (TTF) model includes five key constructs: task characteristics, technology characteristics, task-technology fit, technology utilization, and performance impact. Task and technology characteristics define specific task and technology dimensions, while task-technology fit reflects users' perceptions of how well the two align the model is based on three propositions: first, task-technology fit is shaped by both task and technology characteristics, measured by factors such as quality, compatibility, and ease of use. Second, technology utilization depends on the perceived fit between task and technology. Finally, a positive task-

technology fit not only predicts utilization but also enhances individual performance (Goodhue & Thompson, 1995).

Research has consistently documented that a poor fit between task and technology can lead to interruptions during technology use, which may ultimately result in technology abandonment This suggests that task-technology fit can significantly influence clinicians' behavioural responses to e-health technologies, particularly in terms of decision-making regarding digital-health acceptance (Marikyan & Papagiannidis, 2023).

The TTF theory and its subsequent extensions have several limitations. One of the key challenges is the complexity of the models, which makes them difficult to test empirically. Furthermore, the theory exhibits weak predictive power and lacks sufficient focus on situational and personal factors. A significant shortcoming of the original TTF model is that its multi-dimensional constructs limit its applicability across various contexts and scenarios. As a result, there are few studies that have comprehensively tested all dimensions of task-technology fit (Alyoussef, 2023; Teo & Men, 2008).

The Task-Technology Fit (TTF) model highlights the importance of aligning task requirements with technology capabilities to improve performance and technology utilization. While it offers valuable insights, the model's complexity and limited applicability across different contexts pose challenges. Future research should focus on addressing these limitations to enhance its practical use.

3.5 Summary

This chapter discussed theoretical models commonly used to understand technology acceptance. It highlighted their limitations and the need for added variables and contextualisation. The chapter also introduced the goal of extending the UTAUT model for studying technology acceptance among AOD workers concerning digital health alongside of the

consideration for a co-design approach for digital health. Overall, it supplies a foundation for the later chapters on empirical investigation and findings in this area. The following table 4 provides a comparative analysis of these theories, critically evaluating their strengths and limitations in the adoption of digital health technologies and their applicability in substance use treatment settings

Table 4 Critical Comparison of Technology Acceptance Theories for Digital Health Adoption and Substance Use Treatment Applications

Theory	Key Constructs	Strengths	Limitations	Applications in Digital Health/Substance Use
Theory of Reasoned Action (TRA) (Ajzen&Fishbein, 1980; M. Fishbein, 1979)	**Attitude Toward Behaviour**: Overall positive or negative feeling about performing the behaviour - **Subjective Norms**: Perceived social pressure to perform or not perform the behavior - **Behavioral Intention**: Motivational factors that influence behaviour.	**Simplicity**: Straightforward to apply. - **Predictive**: Useful for understanding intention-based behaviours in various contexts.	**Assumes Volitional Control**: Presumes that individuals have complete control over their behaviour. - **Limited Flexibility**: Less effective in explaining behaviours influenced by external or unconscious factors	**Digital Health**: Applied to predict user intentions in adopting digital health interventions, such as mobile health apps (Asvinigita, Piartrini, Suprapti, & Widagda, 2022) - **Substance Use**: Limited by its assumption of volitional control, which can be problematic in contexts where external factors like addiction or social stigma play a significant role (Tavousi, Montazeri, Hidarnia, Hajizadeh, Taremian, & Haerimehrizi, 2015).
Theory of Planned Behaviour (TPB) (Ajzen, 1991).(Ajzen, 1991).	**Attitude Toward Behaviour**: Degree to which a person has a favourable or unfavourable evaluation of the behaviour - **Subjective Norms**: Influence of social pressure (Ajzen, 1991). - **Perceived Behavioral Control**: Perception of ease or difficulty in performing the	**Incorporates Control**: Adds perceived Behavioral control, making it more comprehensive than TRA. - **Broader Applicability**: Effective in predicting behaviours in contexts with varying levels of control).	**Rational Assumption**: Overemphasizes rational decision-making, ignoring emotional and unconscious influences - **Static**: Less effective in dynamic environments where behaviour and intentions may change over time.	**Digital Health**: Extensively used to predict adoption of digital health tools, such as telemedicine or health apps (Sadoughi, Khodaveisi, & Ahmadi, 2019). - **Substance Use**: Helps understand technology use in situations with limited control, though it may not capture the full range of factors influencing behaviour in substance use contexts, such as emotional states or external pressures

	behaviour - **Behavioral Intention**: Intent to perform the behaviour.			(Bonny-Noach, Gold, & Caduri).
Technology Acceptance Model (TAM) (Davis, 1985)	**Perceived Usefulness (PU)**: Belief that using technology will enhance performance - **Perceived Ease of Use (PEU)**: Belief that using technology will be free from effort (Davis, 1989). - **Behavioral Intention**: Intent to use technology based on PU and PEU	**Widely Applicable**: Simple and adaptable across various settings. - **Strong Predictive Power**: Particularly effective in predicting technology adoption	**Ignores Social Factors**: Overlooks social influences and emotional aspects of technology adoption. - **Narrow Focus**: Concentrates on cognitive aspects, potentially missing broader behavioural influences	**Digital Health**: Frequently applied to assess the acceptance of digital health technologies among both patients and healthcare providers (Rahimi et al., 2018). - **Substance Use**: While useful, its focus on usefulness and ease of use may overlook critical factors like trust, privacy concerns, and the social stigma often associated with substance use treatment technologies.
Diffusion of Innovation (DOI) (J. Kaminski, 2011; E. M. Rogers, 1983).	**Innovation**: Perceived newness and value of the technology. - **Time**: Rate at which the innovation is adopted **Communication Channels**: Means by which information about the innovation is spread - **Social System**: Social structure affecting the diffusion of innovation	**Broad Explanatory Power**: Explains how innovations spread across social systems. - **Identifies Adoption Stages**: Recognizes different adopter categories (e.g., innovators, early adopters).	**Complex Measurement**: Difficult to quantify human networks and interactions - **Lacks Depth**: Does not fully explain the processes behind technology acceptance and rejection.	**Digital Health**: Used to understand the adoption of digital health innovations within healthcare communities(P. L. Kaminski, 2011) - **Substance Use**: Helps explain the spread of digital tools in substance use treatment settings, though it may not fully capture the nuanced factors that influence adoption in these complex environments (Elison, Ward, Davies, & Moody, 2014).
Technology-Organization-Environment (TOE) (Tornatzk	**Technological Context**: Available technologies and their characteristics (Tornatzky,	**Organizational Focus**: Offers a comprehensive view at the organizational level.	**Limited Individual Focus**: Does not account for individual user behaviour. - **Generic**: Can	**Digital Health**: Useful for analysing how healthcare organizations adopt digital health technologies(Baker, 2012) - **Substance Use**: Relevant for

y, Fleischer, & Chakrabarti, 1990).	Fleischer, & Chakrabarti, 1990). - **Organizational Context**: Organizational size, structure, and resources - **Environmental Context**: External factors such as competition, regulation, and market structure	- **Environmental Consideration**: Includes external pressures and influences	be too broad, lacking specificity for certain contexts	understanding organizational adoption of technologies in SUD treatment but may overlook individual-level factors like clinician or patient resistance.
Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)	**Performance Expectancy (PE)**: Belief that using technology will lead to gains in job performance - **Effort Expectancy (EE)**: Ease of use associated with the technology - **Social Influence (SI)**: Degree to which others influence one's use of the technology - **Facilitating Conditions (FC)**: Belief that organizational and technical infrastructure supports use - **Moderators**: Factors like age, gender, experience, and voluntariness that influence the impact of the four key constructs	**Comprehensive Integration**: Combines elements from multiple models, providing a robust framework. - **High Predictive Accuracy**: Strong in predicting both intentions to use and actual use	**-Complexity**: Includes many constructs, which may require contextual adaptation. - **Need for Extension**: May need additional factors (e.g., trust, risk) to fully explain technology acceptance in specific contexts	**Digital Health**: Extensively applied to understand the acceptance of digital health tools, such as mHealth apps and telehealth services (Cimperman, Makovec Brenčič, & Trkman, 2016). - **Substance Use**: Provides a strong framework for studying technology adoption in SUD settings, though additional factors like trust and perceived risk may need to be integrated to fully capture the unique challenges in these environments(R. Menon, Meyer, Nippak, & Begum, 2022).

3.5 Conceptual Model

3.5.1 Overview

This research acknowledges that a multitude of factors may affect the success and effectiveness of digital health acceptance among Alcohol and Other Drugs (AOD) workers in Australia. Certain elements contributing to this acceptance may not have been adequately captured in the existing literature, mainly because most studies focus on contexts outside of substance use disorder (SUD) treatment in Australia.

A rigorous review of the relevant healthcare literature indicates that the Unified Theory of Acceptance and Use of Technology (UTAUT) presents a suitable framework for understanding technology acceptance. However, this model might necessitate further adaptation or extension to fit Australia's unique context of the AOD workforce. This section introduces and substantiates the application of the UTAUT framework, building and extending it by integrating it with the most relevant contextual predictors of acceptance specific to the AOD workforce, including aspects such as trust.

Furthermore, this section will delineate the rationale for the relationships posited within the research model. It will culminate in formulating hypotheses and a detailed definition of the constructs underpinning the research, concluding this chapter. The aim is to provide a robust and contextually adapted conceptual model that effectively aids in understanding and enhancing digital health acceptance among AOD workers in Australia.

3.5.2 Theoretical Foundation of The Conceptual Model

Technology acceptance in healthcare is a dynamic and unique area, setting itself apart from its application in government, education, or business sectors (Hermes, Riasanow, Clemons, Böhm, & Krcmar, 2020). While the Technology Acceptance Model (TAM) is highly regarded within health-related industries, the Unified Theory of Acceptance and Use of Technology

(UTAUT) emerges as a more apt framework for this study. UTAUT not only encompasses eight other theoretical models, including TAM but also provides a more comprehensive method for understanding human interaction with technology. However, to effectively apply UTAUT to the specific context of digital health in Substance Use Disorder (SUD) treatment in Australia, a tailored modification of the model is necessary, as suggested by (Venkatesh et al., 2003)

Such an adapted framework presented in Figure 19 offers an expansive base for clinicians, facility managers, and policymakers to understand and influence the acceptance of digital health tools. This insight enables the development of targeted interventions, enhances client engagement, and optimizes treatment outcomes in the complex and critical field of healthcare and substance treatment.

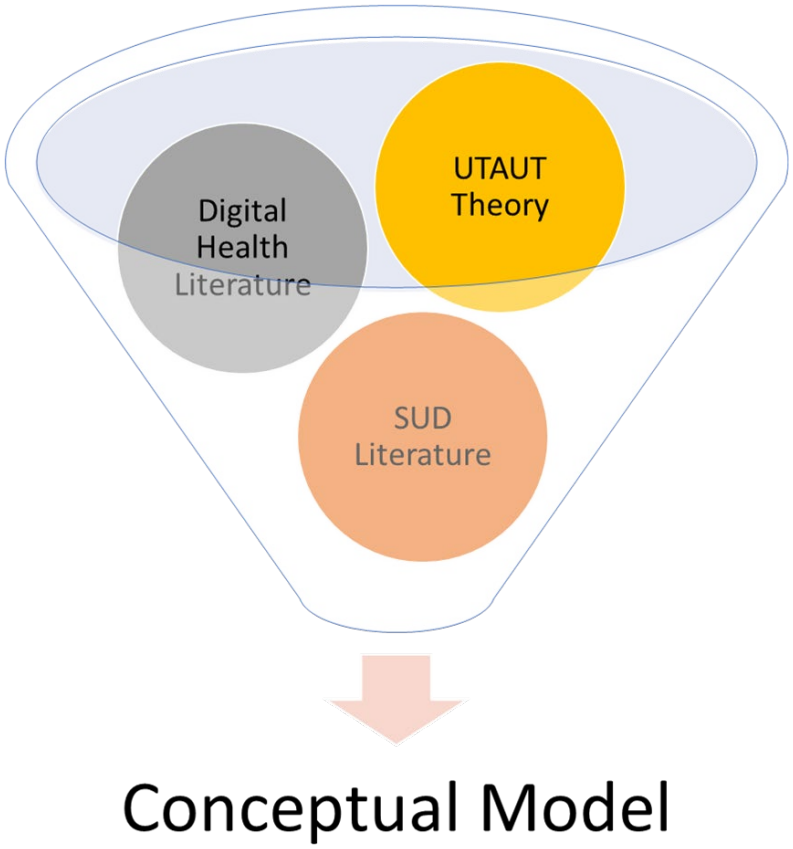

Figure 19 Elements of Conceptual Model

3.5.3 Behavioural Intention (BI) and Actual Use

The main theories developed to explain the end-user acceptance of modern technology, such as TAM2 (Venkatesh & Davis, 2000) or UTAUT (Venkatesh et al., 2003), claim that behavioural intention is a reasonable alternative to actual use behaviour (Chau & Hu, 2002). The BI, the "conative component of attitude," is considered vital to real action (Ajzen & Fishbein, 1975b, 1977). A systematic literature review uncovered 73 relevant empirical studies in 79 articles, indicating a likely correlation between Behavioral Intention (BI) and actual usage (M. Turner, Kitchenham, Brereton, Charters, & Budgen, 2010).

In this study, four moderators (age, gender, experience, and voluntariness of use) had been included from the original UTAUT model. According to the 2019-2020 national AOD workforce survey by Skinner (2020), 69% of AOD workers were females, 76% were 36 years old or older, and 41% had ten or more years of experience (Skinner, McEntee, & Roche, 2020a). Previous research has also demonstrated associations between younger age, male gender, and years of professional experience with higher digital health acceptance (Mahmood, Kedia, Wyant, Ahn, & Bhuyan, 2019). These findings, which will be reported in the relevant section, underscore the importance of considering demographic factors when assessing technology acceptance among AOD workers

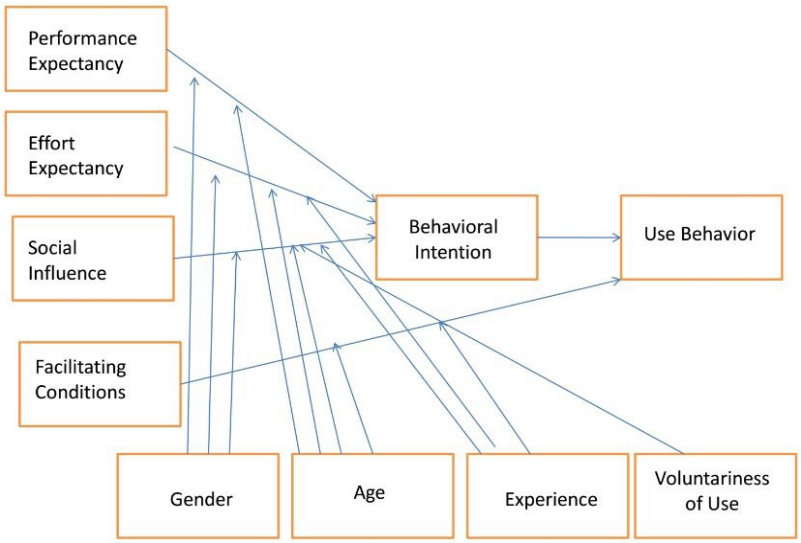

Figure 20 Theoretical Foundation

3.6 UTAUT Acceptance Predictors

3.6.1 Performance Expectancy and Effort Expectancy

Performance Expectancy (PE) refers to clinicians' belief that digital tools will improve their job performance. Effort Expectancy (EE) pertains to the perceived ease or simplicity of using these digital tools. PE is the most substantial factor contributing to a user's behavioural intention (BI) in implementing digital means (Venkatesh et al., 2003).

In the context of this research:

EE represents clinicians' expectations regarding the user-friendliness of digital tools.

PE signifies their belief that using such tools will improve their job effectiveness.

The present research hypothesises that PE and EE could significantly influence clinicians' behavioural intention to accept digital health. To examine these relationships, the study proposes the following hypotheses:

Hypothesis 1: There is a direct and positive relationship between EE and BI of AOD clinicians using digital health.

Hypothesis 2: There is a direct and positive relationship between PE and BI of AOD clinicians using digital health.

3.6.2 Social Influence

Social Influence (SI) refers to a clinician's perception that significant others believe they should utilise Information and Communications Technology (ICT). The effect of this construct on the behaviour of AOD practitioners is channeled through compliance identification and internalisation, and the direct impact of this variable on behavioural intention has been demonstrated in Technology Acceptance (TA) studies (Venkatesh & Davis, 2000).

According to the current national survey (Skinner, McEntee, & Roche, 2020a), AOD workers are not a large community within the health sector and do not operate independently like physicians. However, they often form part of an allied health team. As a result, social norms and pressures can play a vital role in determining their level of digital health acceptance. Based on this understanding, the following hypothesis is proposed:

Hypothesis 3: There is a direct and positive relationship between social influence and the Behavioral Intention (BI) of AOD clinicians using digital health.

3.6.3 Facilitating Conditions

Facilitating Conditions (FC) encompass two significant components. The first includes technical support, characterising an individual's resources and skills, and the second pertains to organisational support involving external factors (Gagnon et al., 2003). The availability of administrative support, such as helpdesk and training, has been reported to mitigate the challenges of communication with clients and clinicians' workflow (Deokar & Sarnikar, 2016).

FC has been recognised as a determinant of Behavioral Intention (BI) (Hoque & Sorwar, 2017). Consistent with this approach, this study hypothesises that FC directly and positively impacts BI, excluding the actual use. Consequently, the following hypothesis is proposed:

Hypothesis 4: There is a direct and positive relationship between facilitating conditions and the Behavioral Intention (BI) of AOD clinicians using digital health.

3.7 Contextual Acceptance Predictors

While the Unified Theory of Acceptance and Use of Technology (UTAUT) offers a substantial foundational framework, it lacks specific considerations for the unique technology, potential clients, and Substance Use Disorder (SUD) context central to this study. To accommodate these distinctive elements and examine the novel ways AOD practitioners adopt digital tools, this study

identifies six SUD context-related predictors of acceptance, informed by a comprehensive literature review and pertinent studies in this field. These include trust in digital health, geographic location, fear of COVID-19, clinician self-efficacy, client e-literacy and access, and the possibility of establishing a therapeutic alliance or virtual intimacy. Integrating these specific predictors into the existing UTAUT framework aims to provide a more refined understanding of technology acceptance in the unique context of SUD treatment.

Incorporating these contextual factors into the UTAUT model aims to enhance the understanding of technology acceptance among AOD practitioners in SUD treatment. These predictors are essential to effectively supporting digital health adoption and implementation in this domain.

3.7.1 Trust in Technology

Given the inherent uncertainties associated with online platforms, trust is a critical determinant in the Behavioral Intention (BI) to use digital health technologies (Al-Adawi, Yousafzai, & Pallister, 2005). The unique attributes of digital health, such as global information access, cybersecurity concerns, intangibility, and spatial/temporal separation in online interactions, amplify these uncertainties (Bomil & Ingoo, 2003; Zaabar, Cheikhrouhou, Jamil, Ammi, & Abid, 2021). Therefore, trust is highlighted as a foundational element influencing technology acceptance and subsequent use (Beldad & Hegner, 2018).

The concept of trust in digital health is debated among scholars. While some argue that trust is exclusively human and cannot be attributed to technology, others suggest that as technology increasingly emulates human behaviour, it may be perceived as a tool and a social companion, potentially altering our trust perceptions (Lankton, McKnight, & Tripp, 2015).

In technology, trust is often equated with the absence or minimal occurrence of technical errors (Ehrismann & Stegwee, 2015). As emphasised by Philip J. Nickel (2010), the reliability of e-tools stands out as a coveted feature (Nickel, Franssen, & Kroes, 2010). In this context,

technical reliability pertains to the likelihood of a service undergoing system faults or encountering other failures.

Within the e-health discipline, numerous studies underscore the significance of trust as a pivotal factor influencing technology acceptance and trust in digital health is imperative for medical professionals' effective assimilation and utilisation of eHealth record systems (Alazzam, Basari, Sibghatullah, Ibrahim, Ramli, & Naim, 2016). Similarly, Tung (2008) incorporated trust into the Technology Acceptance Model (TAM) to gauge nurses' intention to utilise electronic logistics information systems across ten medical centres in Taiwan. Their findings robustly corroborate the positive influence of trust on Behavioral Intention (BI) to use the system (Tung, Chang, & Chou, 2008). Further, technical glitches, identified as a significant impediment to eHealth acceptance, could escalate time, cost investments, and safety (Adjekum, Blasimme, & Vayena, 2018). Consequently, the study proposes the ensuing hypothesis.

Hypothesis 5: There is a direct and positive relationship between the reliability of e-tools (trust) and BI of AOD clinicians using digital health.

3.7.2 Clinician's Self-Efficacy

Computer self-efficacy is fundamentally linked to individual performance, the success of information systems, and organisational competitiveness. It is defined as an individual's belief in their capacity to effectively utilise computers and technology, significantly impacting their ability to perform successfully (Compeau & Higgins, 1995). Bandura (1986) describes self-efficacy as the conviction about one's ability to execute specific behaviours. This concept holds particular importance in the context of clinicians' adoption and effective use of digital health technologies (Balapour, Reychav, Sabherwal, & Azuri, 2019). It implies that clinicians' belief in technological capabilities can influence their engagement and proficiency with digital health tools.

Research indicates a strong correlation between self-efficacy and technology acceptance, particularly highlighting that individuals with higher self-efficacy find technology more

straightforward to use and are more likely to adopt it due to positive performance expectations. High self-efficacy leads to a perceived ease of use and enhances the impact of perceived usefulness on adoption intention. Users confident in their abilities view new systems, like mobile health, as more manageable and beneficial and, thus, are more inclined to incorporate such technologies into their routines. (Y. Liu, Lu, Zhao, Li, & Shi, 2022; Xiaofei Zhang, Han, Dang, Meng, Guo, & Lin, 2017). Given these insights, this study proposes focused hypotheses examining the extent to which self-efficacy influences technology acceptance, aiming to understand and potentially amplify the adoption of innovative systems through the lens of user self-perception. Thus, the following hypothesis is suggested:

Hypothesis 6: There is a direct and positive relationship between clinicians' self-efficacy and BI of AOD clinicians using digital health.

3.7.3 Geographical Location

Geographical location significantly influences technology acceptance, especially in the context of health care. Factors like long distances, poor road conditions, social isolation, and limited services exacerbate access to care issues, particularly in rural and remote areas. Additionally, in smaller communities, concerns over stigma, embarrassment, and privacy related to sensitive issues like substance use disorder (SUD) can deter individuals from seeking help (Campo & Tayton, 2015). Moreover, attracting and retaining medical and allied health professionals in these regions is challenging, with the scarcity becoming more pronounced with increased remoteness (Wilson, Couper, De Vries, Reid, Fish, & Marais, 2009). These geographical disparities contribute to differing attitudes and acceptance levels towards digital health solutions among populations, indicating the need for targeted strategies to enhance technology adoption in varied settings (Chipeva, Cruz-Jesus, Oliveira, & Irani, 2018).

Several studies highlight how geographical location impacts technology acceptance. Research spanning the United States, Saudi Arabia, China, and South Korea indicates notable

variations in technology acceptance rates across different regions (Venkatesh & Zhang, 2010). A focused quantitative study across five rural Nigerian states involving 25 health facilities found significant differences in the perceived ease of use and usefulness of technology in healthcare (Jimoh et al., 2012). In the US, a survey covering 12,334 treatment facilities from 2016 to 2019 revealed that rural areas, while diverse in their client and treatment types, significantly correlate with increased telemedicine adoption (Uscher-Pines, Cantor, Huskamp, Mehrotra, Busch, & Barnett, 2020). These studies collectively emphasize the crucial role of geographic factors in shaping technology acceptance, particularly in healthcare, paving the way for this study to propose hypotheses to explore further how geography influences technology adoption. Therefore, this study proposed the following hypothesis:

Hypothesis 7: There is a direct and positive relationship between the remoteness of geographical location and BI of AOD clinicians using digital health.

3.7.4 Fear of COVID-19

SARS-CoV-2 (COVID-19) has profoundly altered healthcare delivery, accelerating the development and utilization of digital solutions. The need for distancing, safety, and rapid communication in healthcare services largely drove this shift. Despite technological advancements, the pandemic has induced widespread psychological distress, anxiety, and fear, significantly disrupting daily routines (C. H. Liu, Zhang, Wong, Hyun, & Hahm, 2020). It's anticipated that the psychological impact of the pandemic may exceed the direct health effects, with increased incidents of domestic violence, phobias, severe disease fear, substance use disorder (SUD), and suicides(Campbell, 2020; Mamun & Griffiths, 2020)

Pre-COVID-19, digital health was seen as a future-oriented approach to enhancing accessibility and quality of care. However, the pandemic has rendered it essential and indispensable, with nearly 72% of users reporting a change in healthcare utilization since its onset (King et al., 2022). The fear and urgency to mitigate COVID-19 risks have significantly

boosted technology acceptance, leading to widespread adoption of virtual visits, faster results reporting, and overall increased reliance on digital health platforms (Clipper, 2020)

The pandemic has also heightened the vulnerability of clients in SUD treatment. Even before the pandemic, access to treatment was challenging, but the situation has worsened with increased risk factors like tobacco or vape use and overcrowding in living spaces (McDonnell et al., 2021). Additionally, the stigma associated with SUD and confusion between COVID-19 symptoms and substance withdrawal has delayed seeking medical help (Dunlop et al., 2020). Consequently, the pandemic has necessitated a swift adaptation to digital health among AOD workers and facilities. This study, therefore, proposes the following hypothesis to understand and address the accelerated shift towards digital health in the wake of COVID-19.

Hypothesis 8: There is a direct and positive relationship between the fear of COVID-19 and BI of AOD clinicians using digital health.

3.7.5 Client Digital Health Literacy and Access

Digital solutions aimed at enhancing access to healthcare and improving its quality may inadvertently overlook the populations most in need of such interventions. The effectiveness of any high-quality care system is fundamentally reliant on its clients. A client-centred approach underscores the importance of delivering care that respects and responds to each patient's unique preferences, needs, and values. This ensures that these principles are central in guiding all clinical decisions (Frampton, Charmel, & Guastello, 2013). In SUD treatment, e-interventions are notably interactive, necessitating active cooperation between clients and clinicians. Clients must be adept at navigating the e-care system, utilising electronic tools (e-tools), and managing their own needs effectively (Ashford, Bergman, Kelly, & Curtis, 2020).

Digital health for Substance Use Disorder (SUD) presupposes that clients possess the ability to comprehend complex written and verbal materials. However, suppose clients struggle to understand digital health information. In that case, their likelihood of undertaking essential

actions for managing their substance dependency or making informed decisions diminishes (Garett & Young, 2023). Notably, difficulties in understanding health information are not exclusive to individuals with lower educational levels; even those with higher education may encounter challenges (Dickens, Lambert, Cromwell, & Piano, 2013).

Several studies have tested the relationship between digital health literacy, perceived ease of use and performance expectancy (Chang, Chao, Yu, & Lin, 2021; Xi Zhang, Yan, Cao, Sun, Chen, & She, 2018).Despite that, clients' digital health access and availability are also critical. The practical accessibility and reliability of clients' mobile and internet services shape the quality of the derived e-intervention (Ramsey, Davidov, Levy, & Abildso, 2022) (Ramsey et al., 2014). Research demonstrated that working with clients with more reliable ICT access predicted clinician acceptance (Anton & Jones, 2017).

Thus, in the context of this research, the study hypothesis

Hypothesis 9: There is a direct and positive relationship between the client's health literacy and access (phone/WIFI/Credit) and BI of AOD clinicians using digital health.

3.7.6 Possibility of Establishing a Therapeutic Alliance and Virtual Intimacy

Typical human interactions, traditionally achieved through face-to-face contact, often face challenges when replicated through electronic tools (Mallen, Day, & Green, 2003). Therapeutic alliances, crucial in therapy, are defined as the "quality of partnership and mutual collaboration between a therapist and client." This alliance is characterised by three primary elements: (1) the establishment of an emotional bond and relationship, (2) agreement on therapeutic tasks, and (3) consensus on therapy goals. Positive evaluations of such alliances in standard face-to-face therapy strongly predict successful treatment outcomes (Flückiger, Del Re, Wampold, & Horvath, 2018; D. J. Martin, Garske, & Davis, 2000).

Furthermore, the therapeutic alliance is labelled as one of the truly stout forecasters of therapy outcomes in psychotherapy (Najavits, Crits-Christoph, & Dierberger, 2000). While research indicates that digital health tools do not necessarily undermine the therapeutic alliance (Richards & Simpson, 2015; Stiles-Shields, Kwasny, Cai, & Mohr, 2014) , concerns persist among practitioners that technology might undermine therapeutic boundaries, restrict treatment planning flexibility, and impede the dynamic interpersonal nature of therapy (Berger, 2017; Richards, Simpson, Bastiampillai, Pietrabissa, & Castelnuovo, 2018) Consequently, this study proposes:

Hypothesis 10: There is a direct and negative relationship between the lack of a therapeutic alliance and the BI of AOD clinicians using digital heal

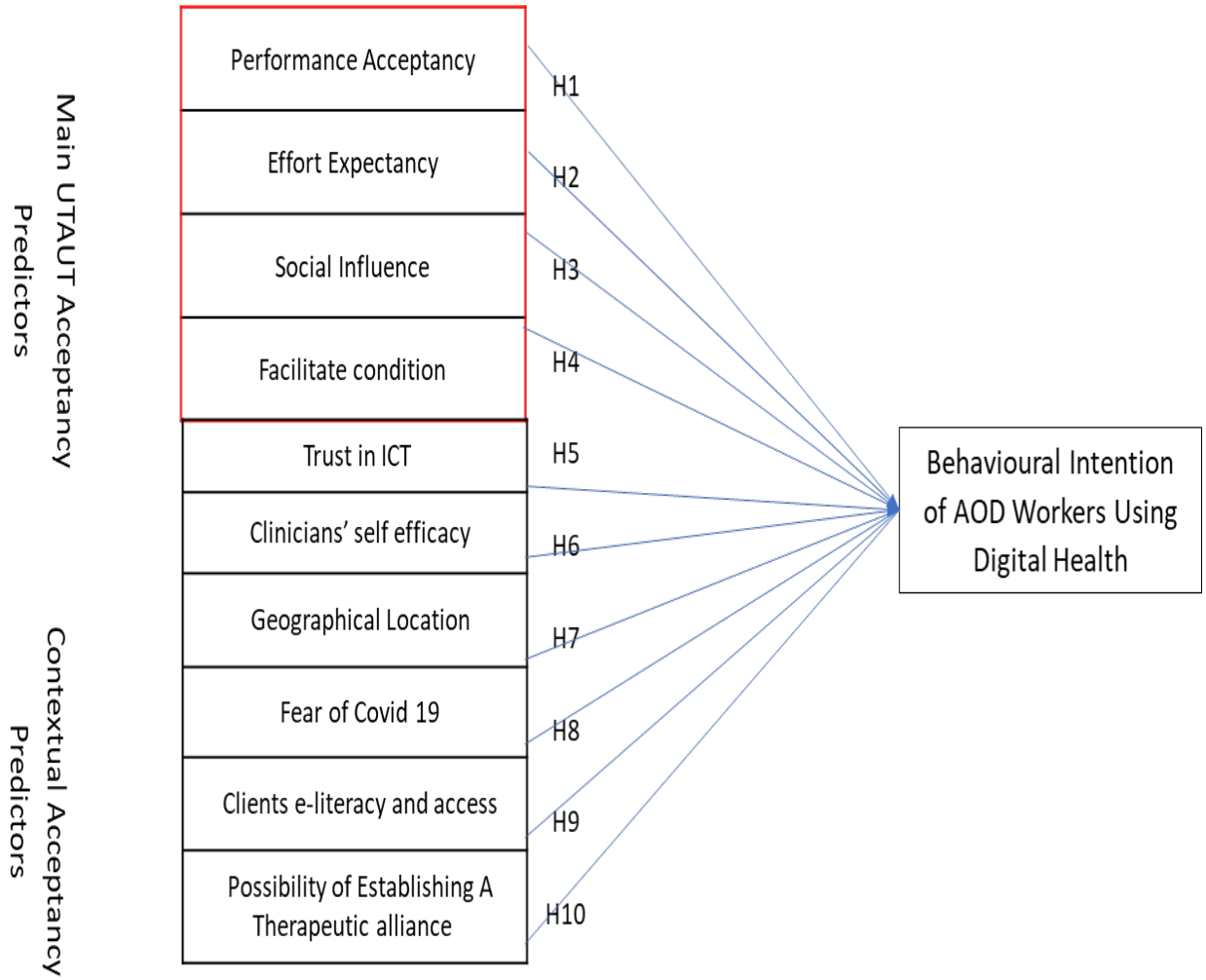

Figure 21 Proposed Conceptual Model

Table 5 Conceptual Model Contracts Definitions

Performance Expectancy (PE): The degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003).
Effort Expectancy (EE): The degree of ease associated with the use of the system (Venkatesh et al., 2003).
Social Influence (SI): The degree to which an individual perceives that important others believe he or she should use the new systems (Venkatesh et al., 2003).
Facilitating Condition (FC): consumers' perceptions of the resources and support available to perform a behaviour (Venkatesh et al., 2003).
Trust (TR): to believe that an e-tool, machine, or equipment will not fail (Sheridan, 2002).
Privacy Concern (PC): "the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others" (Chai et al., 2009).
Self-efficacy (SE): is one's belief in one's ability to execute a particular task (V. Venkatesh &Davis, 1996).
Fear of COVID-19(FC19): The sharp increases in fear and worries relating to the virus (Asmundson & Taylor, 2020a; McCarthy, 2020). Fear is defined as an unpleasant emotional state that is triggered by the perception of threatening stimuli (de Hoog et al., 2008).
Digital Literacy (DL): the set of skills needed to find, retrieve, analyse, and use information" ACRL (2007).
Digital accessibility Barriers (AB): the extent to which a product, device, service, or environment is available and navigable for persons with special needs or functional limitations (Lazar et al., 2015).
Geographic location (GL): specific physical point on Earth. The physical area wherein the statistical unit (e.g., individual) is located. Erkin, G., & Shakhrizoda, H. (2022).
Therapeutic Alliance (TA): the concepts of transference and countertransference, which are the unconscious feelings or emotions that a patient feels towards their therapist, and vice-versa (Freud S., 1912).

Table 6 Hypotheses

Number	Hypotheses
H1	There is a direct and positive relationship between effort expectancy (EE) and behavioral intention (BI) of alcohol and other drug (AOD) clinicians using digital health technologies.
H2	There is a direct and positive relationship between performance expectancy (PE) and behavioural intention (BI) of AOD clinicians using digital health technologies.
H3	There is a direct and positive relationship between social influence and the behavioural intention (BI) of AOD clinicians using digital health technologies.
H4	There is a direct and positive relationship between facilitating conditions and the behavioural intention (BI) of AOD clinicians using digital health technologies.
H5	There is a direct and positive relationship between the reliability of e-tools (trust) and the behavioural intention (BI) of AOD clinicians using digital health technologies.
H6	There is a direct and positive relationship between clinicians' self-efficacy and the behavioural intention (BI) of AOD clinicians using digital health technologies.
H7	There is a direct and positive relationship between the remoteness of geographical location and the behavioural intention (BI) of AOD clinicians using digital health technologies.
H8	There is a direct and positive relationship between the fear of COVID-19 and the behavioural intention (BI) of AOD clinicians using digital health technologies.
H9	There is a direct and positive relationship between the client's health literacy and access (phone/Wi-Fi/credit) and the behavioural intention (BI) of AOD clinicians using digital health technologies.
H10	There is a direct and negative relationship between the lack of a therapeutic alliance and the behavioural intention (BI) of AOD clinicians using digital health technologies.

3.7.7 Summary

Figure 20 presents the proposed conceptual model for driving technology acceptance in AOD workers. In addition to contextualising UTAUT to digital health, the study extends the theory by integrating contributing factors of the four key situational predictors. The chapter discussed the hypothesis development stemming from the conceptual model. The subsequent chapter will present the study methodology and design.

4- CHAPTER FOUR – METHODOLOGY- QUALITATIVE RESEARCH STEPS

4.1 Overview

This chapter outlines the methodology employed in this study, providing clarification and justification for its selection. The research aims to provide deepen understanding of SUD clinician's digital health adoption in substance treatment settings, a context noticeably different from general healthcare or client usage.

A variety of factors influence clinicians' adoption of electronic tools. This study seeks to identify and analyse the primary factors influencing the adoption of these tools and to develop a comprehensive framework for integrating digital health into SUD treatment environments. The chosen research method is designed to effectively navigate the unique challenges and requirements of collecting, analysing, and interpreting data within this specific context.

The chapter is structured into several keys: research design, the rationale for selecting an exploratory sequential design, research paradigms, population and sampling strategies, and the methodologies, techniques, and instruments employed for data collection. It will also explore the validity and reliability of the selected method and discuss ethical considerations and required approvals.

4.2 Research Design

4.2 Research Design

The terms 'research methods' and 'methodology' are frequently used interchangeably but represent two distinct yet interrelated research components. 'Research methods' are the technical strategies employed in collecting evidence, encompassing practical data generation and analysis techniques. In contrast, 'methodology' refers to the overarching framework and theoretical analysis that guide the research process, encompassing the principles and ideas that

inform and shape the design of a study (Kirsch & Sullivan, 1992). Thus, the methodology provides the philosophical underpinnings for understanding which methods, or technical procedures, are appropriate and how they should be applied (Birks, Coyle, Porter, & Mills, 2011). Therefore, a comprehensive understanding of both methods and methodology is crucial for designing a research study that logically progresses to accumulate the requisite knowledge to address the research questions effectively.

Consequently, this section is dedicated to exploring the most suitable research paradigm and selecting the approach for this study. Under the positivist paradigm, researchers typically adopt a deductive approach, where the inquiry begins with established theories from the literature to formulate hypotheses. These hypotheses are then tested through data collection and analysis, aiming to confirm or refute them. Conversely, the inductive approach, which aligns with interpretivism, prioritises data collection without predetermined theories.

Analysis of this data leads to the development of new theories or models (Knox, 2003). Each approach offers distinct pathways for understanding phenomena, guiding researchers in their methodological choices based on the nature and objectives of their study. Examining a research problem through diverse methods enriches the understanding of the subject matter by facilitating multiple perspectives. This multidimensional approach enables scholars to derive more holistic and nuanced explanations of phenomena (B. Kaplan & Duchon, 1988). Reflecting this principle, the research design adopted in this study is an interdisciplinary mixed methods approach, specifically utilising an exploratory sequential design. This methodological choice is showing in Figure 22, illustrating how the study sequentially integrates qualitative and quantitative data to build a comprehensive analysis framework.

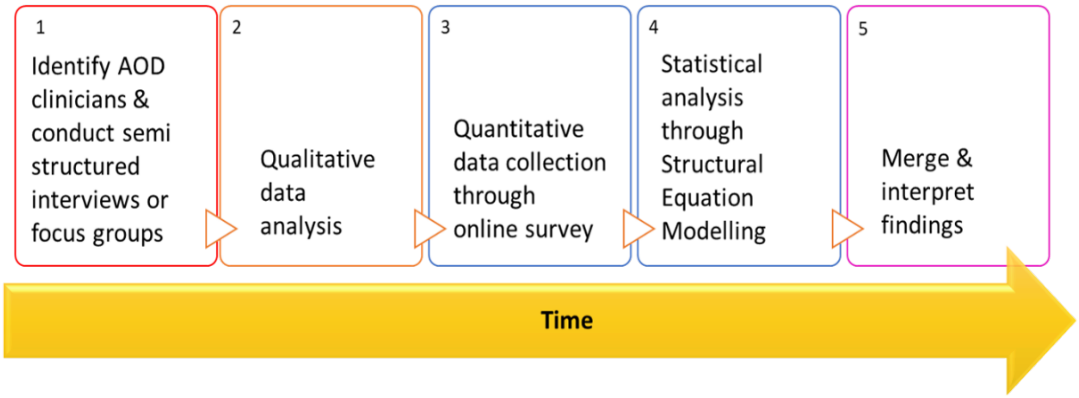

Figure 22 Exploratory sequential design proposed for this study (adapted from Creswell (2014)

4.2.1 Multidisciplinary Approach

This study adopts an interdisciplinary approach, integrating analytical methods from various disciplines to comprehensively explore the perspectives and challenges AOD workers face in implementing digital health. This method enhances understanding of digital health adoption in SUD treatment settings.

Digital Health Discipline

This thesis incorporates insights from technology acceptance literature, mainly focusing on digital health amid the rapid advancements in ICT and digital health technologies promising for care integration. Efforts to adapt evidence-based psychosocial interventions into digital platforms (e.g., apps, web-based services, and smart devices) are increasing, introducing new potential in the SUD field. Despite their nascent application in SUD treatment, these digital tools show significant promise for impactful contributions to substance dependency management, as documented in earlier chapters. Digital interventions offer the possibility of real-time, seamless bio-psychosocial monitoring and continuous, tailored support for SUD clients and clinicians (McDonnell et al., 2021).

Social Work Discipline

Social workers have historically played and continue to play a pivotal role in SUD treatment as addiction specialists, administrators, care managers, policymakers, and advisers. They are key in selecting, implementing, or advocating for evidence-based treatments across various settings. Their work spans the full recovery continuum, from initial motivation through outpatient recovery to long-term rehabilitation and abstinence (Daley & Feit, 2013).

Social work practice is inherently interdisciplinary, integrating knowledge from sociology, psychology, human biology, political science, health, community development, law, and economics. It engages with individuals, families, groups, and communities at both micro and macro levels, employing a bio-psychosocial approach and various theoretical frameworks (L. Turner, 2005). In SUD settings, social workers are crucial members of interdisciplinary teams, collaborating with mental health clinicians, child welfare caseworkers, teachers, counsellors, legal advocates, physicians, and criminal justice professionals (Linley, Mendoza, & Resko, 2014).

4.2.2 Mixed-Methods Approach

Aligned with the proposed conceptual model, this study will employ a mixed-methods approach, motivated by the limited existing research and the intricate task of identifying the factors influencing AOD clinicians' adoption and acceptance of digital health technologies. A mixed-methods research strategy leverages the strengths of both quantitative and qualitative methodologies (Tashakkori & Teddlie, 2008), combining them to provide a comprehensive understanding of research problems.

While there is no universally accepted definition, mixed-method research typically involves the inclusion and separate examination of both qualitative and quantitative data components within a single study. These components can be integrated either sequentially or concurrently. Further, mixed-methods research combines at least one qualitative analysis, focusing on in-depth

understanding, with one quantitative analysis, emphasising numerical data, to ensure a comprehensive study. This integration is crucial for a thorough investigation, mixing the strengths of both approaches (Green, Creswell, Shope, & Clark, 2007).

For this study, the mixed-method approach is deemed particularly suitable for investigating an issue that has not been explored sufficiently. It begins with a qualitative phase to explore the nuanced perspectives and experiences of AOD clinicians with digital health technologies. This phase aims to unearth preliminary insights and patterns. Subsequently, these findings will be rigorously tested and validated through a quantitative phase, ensuring the depth and breadth of understanding necessary for comprehensive analysis.

4.2.3 Exploratory Sequential Design Model

Based on the identified gaps in the literature review, this research seeks to find the most suitable solution for improving the technology acceptance level of AOD workers in Australia. Hence, an exploratory, sequential, mixed-method design (Tashakkori & Teddlie, 2008) is appropriate. The sequence of the study development follows what Creswell (2009) describes as ‘sequential procedures, in which the researcher seeks to elaborate on or expand the findings of one method with another method’ (p.16). Hence, it consists of a primary qualitative phase to shape the following quantitative phase, as demonstrated in Figure 23.

Phase 1: Semi-structured interviews with AOD workers.

Phase 2: Quantitative Online Survey of AOD Workers.

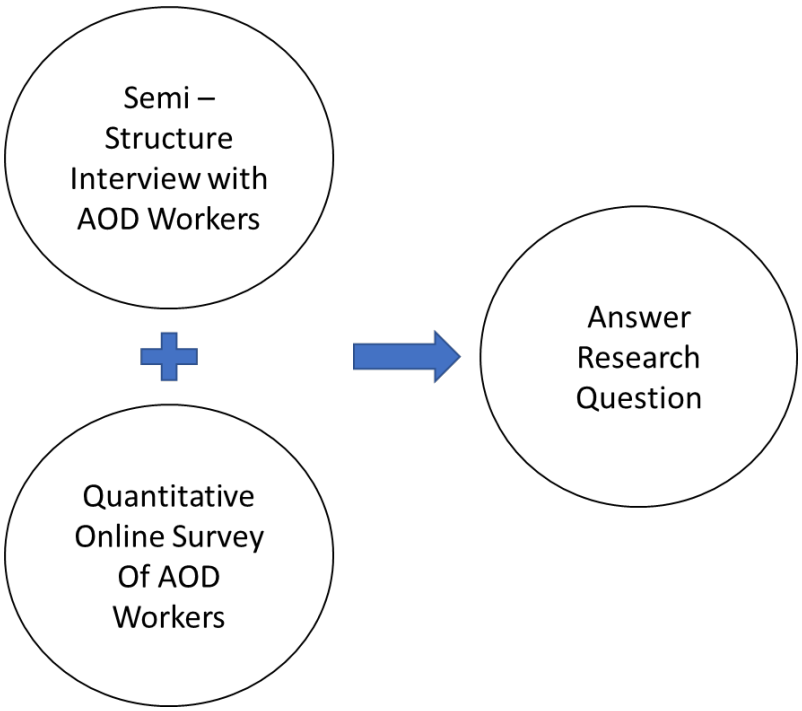

Figure 23 Interviews and Questionnaires Adopted in Research

Justification for Exploratory Sequential Design Model

This study aims to understand and identify the factors that influence the acceptance and use of digital tools through the UTAUT model as the underlying theory and extend it using digital health and SUD factors. Thus, the researchers need to explore the relevance of these new factors in the model and test their significance to contribute to theory development.

Qualitative and quantitative methods have disadvantages and advantages; combining them helps to gain an in-depth understanding of the research problem. E-health is still a relatively embryonic field, so the qualitative method is suitable for this research since little is known about the questions being studied (Tashakkori & Creswell, 2007). Quantitative research is then valuable for robustly testing the model. Consequently, the rationale for employing a mixed approach is two-fold. Firstly, the qualitative phase will assist with refining the conceptual model to

confirm the relevance of factors and the development of the quantitative research instruments. Secondly, the quantitative phase will help validate elements clearly and broaden the results' applicability and generalisability.

Furthermore, the literature review played a crucial role in identifying the core issues associated with the research questions and pinpointing key contextual factors. Additionally, it was an essential step in the creation of the survey tool. In this regard, Figure 23 illustrates the steps of the Exploratory Sequential Mixed-Method.

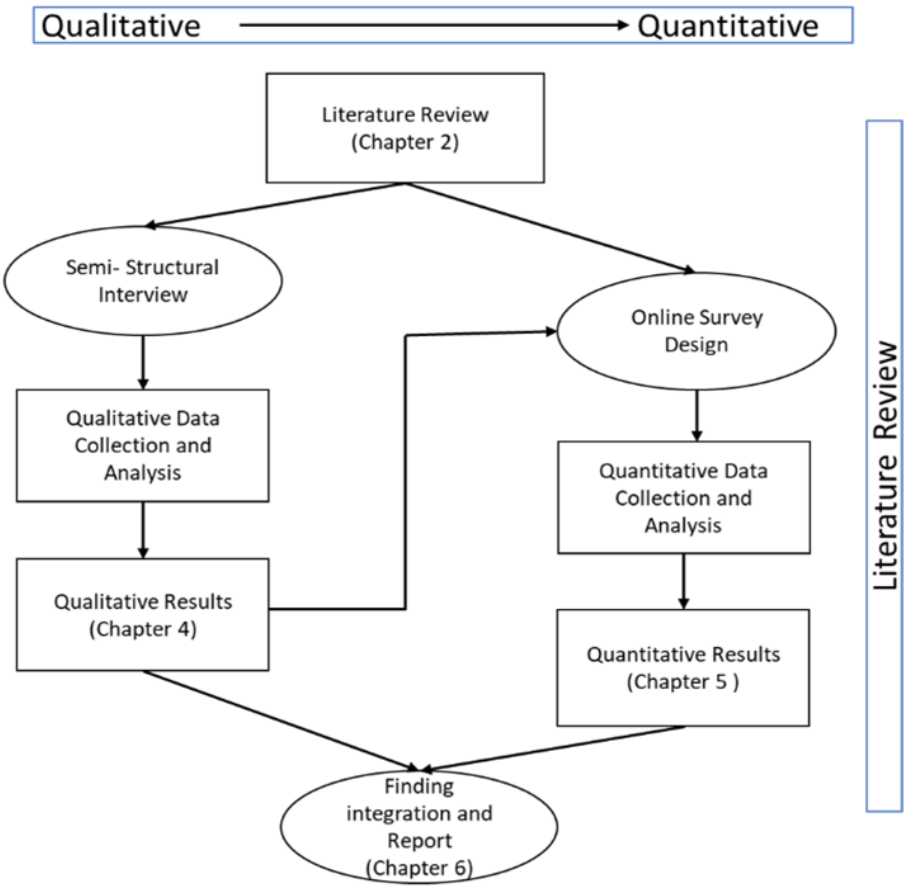

Figure 24 Articulated Exploratory Sequential Mixed Method Research Design of the Thesis

Figure 24 also indicates that the literature review was a continuing, iterative part of this research as factors and dimensions emerged, particularly in the qualitative phase. Further, this review was an indispensable instrument for determining the fundamental concerns in exploring the research problems and discovering the most critical variables. Additionally, it was a necessary step in developing the survey instrument.

4.3. Qualitative Phase Research Methods

4.3.1 Population and Sample

Gray (2009) describes a population as the complete number of probable groups or elements the investigator hopes to incorporate into the research. The targeted population of this study consists of individual adults with diverse professional backgrounds (e.g., social workers, AOD workers, psychologists, counsellors, caseworkers, harm reduction workers, and peer workers) working in alcohol, nicotine, and other drug treatment centres. They have different treatment philosophies (e.g., medication-assisted therapy, harm reduction, abstinence), funding types (private, public, mixed), and geographic locations (rural and metropolitan areas) in Australia. Without engaging the various parties in this study, the result would be restricted to one point of view point It would not draw a thorough and inclusive picture of digital health in Australia.

Potential recruitment sources include online professional networking platforms including LinkedIn, drug treatment and support services websites, peak bodies and stakeholders such as the National Centre for Education and Training on Addiction (NCETA), South Australian Network of Drug and Alcohol Services (SANDALS), Victorian Alcohol and Drug Association (VAADA), Drug and Alcohol Services South Australia (DASSA), Network of Alcohol and other Drugs Agencies (NSW) and others were purposely selected to recruit clinicians who met the following criteria:

- Selection Criteria 1: 18 years old and above
- Selection Criteria 2: Formally employed for a minimum of one year.

- Selection Criteria 3: In direct contact with clients and responsible for delivering any substance treatment in Australia. Those who were retired had less than a year of work experience or were not involved with clients were excluded.

4.3.2 Sampling Methods: Purposive Sampling

This study uses nonprobability sampling, specifically purposive or judgment sampling, due to the study's nature and objectives. This sampling technique identifies and chooses individuals or groups of proficient and well-informed participants with experience and knowledge (J. W. Creswell, 2011). In addition, willingness, availability and the ability to communicate in an articulate, expressive, and reflective manner were required because this research examines the real-life experience of clinicians applying digital health in Australia.

4.3.3 Data Collection Method

Data collecting is critical in research as "good" information (qualitative data) is intended to create knowledge that helps us answer the research questions, explain people's experiences, encapsulate the situation, challenge our previous thinking, and invite additional inquiry. The most vital objective of data collection is ensuring that rich and reliable data is collected so the researcher can make data-driven decisions. The method of data collection is diverse for different fields of study, dependent on the required information. However, regardless of the field of research, in most studies, data collection is the primary and most crucial step (De Pourcq, Gemmel, Devis, Van Ooteghem, De Caluwé, & Trybou, 2019).

Data collection methods are also important because how the accumulated information is used and what descriptions it can produce are established by the methodology and analytic style employed by the scholar (Guest, Namey, & Mitchell, 2013). With their strengths and weaknesses, five essential data collection methods are surveys, interviews, focus groups, observations, and textual or content analysis (Harrell & Bradley, 2009). As the researcher select interviews as a data collection method for this study, the most critical objective is to ensure that

information-rich and reliable data is collected so that data-driven decisions can be made to validate our survey questions and findings.

- ***Semi-Structured Interviews***

In this study, semi-structured interviews were used as the data-collection approach. This is suitable when it is necessary to identify the participants' constructs as a basis for their beliefs and opinions about a specific situation (Easterby-Smith, Thorpe, & Jackson, 2012). Further, it has the benefit of two-way communication, and the researcher can also prepare questions in advance.

In this research, sixteen questions were progressed to obtain in-depth data. The semi-structured interview questions (see Appendix A) were designed to investigate the AOD workers' experience and perceptions regarding e-health use and adoption in Australia. Through one-to-one virtual or face-to-face meetings between the interviewee and researcher, there was the opportunity to investigate additional dimensions of the studied reality and uncover new insights more deeply. The questions were also aimed to assess the current situation, progress and future planning and identify end service users' main challenges. This helps capture the interviewees' real-life experiences and obtain accurate reports. The outcomes of these interviews were employed to complement and restructure the questionnaires. The first and second questions were introductory (e.g., "Tell me about your current position") to build rapport with the contributors (Plas, Kvale, & KVALE, 1996).

To provide a comprehensive set of verbatim comments, the interviews were recorded (Ticehurst and Veal, 2000), and that was beneficial in developing constructs, definitions, and procedures, giving the study novelty. Additionally, instead of being immersed in excessive note-taking, the researcher should allocate time to build a rapport with the interviewees, have eye contact, assimilate the point of discussion, and discover more efficiently (Alshenqeeti, 2014). Utilising digital recorders, with participant consent, enhances this study's methodological rigour and ethical integrity while preparing for technical contingencies. This approach ensures accurate

data capture, allowing for full researcher engagement and effective rapport building without the distraction of note-taking. Brief notes are also taken as a safeguard against potential technical issues, balancing the need for comprehensive data collection with practical considerations (Matheson, 2007). This strategy supports the study's aim to gather deep, nuanced insights, demonstrating a commitment to methodological precision and participant privacy.

- Rationale for Selecting the Number of Interviewees

Selecting an appropriate number of interviewees in the qualitative research phase is critical to gaining in-depth insight into an area and achieving saturation on a theme (Onwuegbuzie, Collins, & Frels, 2013). A small sample can lead to concerns in achieving data sufficiency. More it was indicated that a sample of six interviews might be “sufficient to enable the development of meaningful themes and useful interpretations” (Guest, Bunce, & Johnson, 2006, p. 78). It recommended that 5 to 25 interviews are needed to provide the basis for a study (Creswell, 2007). Thus, 18 interviews were conducted for the present work.

4.4 Validity and Reliability

Validity and reliability are pivotal in ensuring the integrity of research findings. Validity concerns the authenticity of the study's measurements, ensuring they accurately reflect the intended research focus without extraneous influences (Golafshani, 2003). Creswell and Poth (2013) describe "validation" in qualitative research as verifying the accuracy of findings, emphasising detailed descriptions and the researcher-participant relationship to ensure a faithful representation of the studied phenomenon (Creswell & Poth, 2016).

On the other hand, reliability relates to the consistency and reproducibility of data across repeated studies. In the context of technology acceptance models, it specifically refers to the stability and consistency of the measured constructs (Heishman, Singleton, & Pickworth, 2008).

The nuances between validity and reliability are outlined in Table 6, focusing on aspects such as saturation, transferability, accessibility, and consistency of interpretation. Subsection 4.4.1 will further detail the methodologies employed to uphold the validity and reliability of this research's qualitative phase, leveraging various tools and techniques to ensure rigorous and dependable results.

Table 6 Validity and Reliability Principles in Qualitative Research (Leung, 2015)

Validity	Did the study answer the research questions?	**Saturation**	Was the saturation point achieved?
		Transferability	Can the findings be applied to similar situations or circumstances?
Reliability	Are the measurements and results consistent and repeatable?	**Assessability**	Is the thesis process documented and justified adequately?
		Consistency of Interpretation	Is the interpretation verified?

4.4.1 How Validity Achieved

The validity of this study was established by employing several procedures, such as the inclusion of various sampling groups and data blinding. This study included experienced practitioners with more than ten years of service in different treatment settings and the newly graduated population with a few years of experience. Also, practitioners working in non-governmental organisations and clinicians in governmental organisations with truly diverse educational backgrounds and geographical locations. Including diverse respondents led the study to reduce its biases towards only one type of conclusion and established a base for acceptable outcomes (Mohamad, Sulaiman, Sern, & Salleh, 2015).

The other technique applied was to limit the amount of information shared with the participants and ensure the study was not influenced by preconceived ideas. These steps helped to establish the validity of the results gained, proving the accuracy of the qualitative research. Further, the validity of the questionnaire was determined using a panel of experts (supervisors and subject

matter experts) familiar with the SUD field and digital health. They were requested to review the interview questions to ensure they were relevant to the research objectives and clearly worded. Hence, statements that were not optimal were eliminated.

4.4.2 How Reliability Achieved

The reliability of this study was established through two procedures. First of all, the researcher recorded and documented each interview and analysed data using NVIVO 12. Tabulating the interviews aided the collection and assessment processes and the overall results. This strategy allowed for a rapid interpretation of every respondent and observation of the study's progress. The table also assisted in summarising research parameters for a clear conclusion.

The reliability was also assessed through data triangulation: methodological triangulation, investigator triangulation and theoretical triangulation (Golafshani, 2003). This research used theoretical triangulation, which means the researcher applied for other researchers' works in a similar field as a comprehensive literature review to support the findings and claims of the data gathering and analysis method. Furthermore, employed Investigator triangulation to provide an additional layer of reliable stamping to the research. The transparency in the current study is accomplished with detailed documentation throughout the entire development of each chapter so that the aims, objectives, methods and other parts can be assessed and repeated effortlessly and precisely. In addition, the researcher constantly re-examined the interpretations of the data and discussed and evaluated the results with supervisors and student colleagues to confirm the consistency of each interpretation and finding. Hence, other researchers are highly likely to achieve similar conclusions by processing the information accumulated for this thesis.

4.5 Ethical Approval

Ethical considerations are an essential feature of any research design (Neuman,2006). In this study, ethical approval was issued on 09/09/2021 from the Human Ethics Low-Risk Panel of

Flinders University (Approval NO 4656; see Appendix C) and Southern Adelaide Clinical Human Research Ethics Committee on 02/10/2021 (Approval NO LNR/21/SAC/212; see Appendix D) preceding the data collection. Participants were advised that the researcher protected their confidentiality and anonymity. Therefore, no names or other identification methods were used to trace the interviewees' responses. They were also free to withdraw at any time, and they were provided with the researcher and supervisor's contact details in the event of any ethical concerns.

4.6. Analysis of Qualitative Data

Data analysis has been described as the "most complex and mysterious of all of the phases of a qualitative project, and the one that receives the least thoughtful discussion in the literature" (Thorne, 2000, p. 1) . In the health field, comprehensive data analysis can elucidate the complexity of human behaviours, facilitate the progress and employment of effective interventions, and provide voice to the lived experiences of diverse groups of people, which is critical for reliable and actionable knowledge. It is described as systematically arranging and exploring the interview transcripts, observation reports, or other non-textual items accumulated by the researcher to enhance the understanding of the subject (Bogdan & Biklen, 1997). Qualitative analyses involve coding or categorising the data, followed by detecting meaningful patterns, and finally, drawing meaning and constructing a logical chain of evidence (Patton, 2014).

4.6.1 Content Analysis

Various approaches exist to sorting, organising, conceptualising, refining, and interpreting qualitative data. Some common approaches are Content Analysis, Narrative Analysis, Discourse Analysis, Framework Analysis, and Grounded Theory (Leech & Onwuegbuzie, 2008) . In this research, content analysis used as a proposed tool for analysing the interview data.

Content analysis is a common term for several qualitative analytic strategies used to examine text, and it is used to describe the characteristics of the document's content by examining who says what, to whom, and with what effect (Wood, 2006) . It is a systematic categorising method employed for studying substantial amounts of written information to establish patterns and styles of word usage, frequency, relationships, and communication structures (Kitto, Chesters, & Grbich, 2008). Practically, the researcher took one piece of data (one interview, one statement, one theme) and compared it with all others, both different and similar related examining possible relations between data.

Justification for Using Content Analysis

The result from the 18 interviews with clinicians was transcribed into substantial amounts of written text describing how they behave or their point of view about applying digital health in SUD settings. As their experiences are complex, multifaceted, and often carry meaning on multiple levels, content analysis used to systematically categorise written interview information and determine patterns, themes, and relations. This process gives insight into complex and diverse models of clinicians' thoughts in SUD settings. Practically, the researcher took one piece of data (one interview, one statement or one theme) and compared it with all others, either different or similar interviews, examining possible relations between them.

To organise our interviews and make sense of textual data, coding used, by starting with a pre-defined set of codes stemming from the literature (deductive coding) but being open to any new codes that inductively come up and iterate on the codes as sift through. Then, for further transparency in realist analysis, NVivo 12 applied, a computer-assisted qualitative data analysis software (CAQDAS), to create an explicitly documented and evidenced assessment. As other researchers have found, using NVivo might be challenging but does produce the robustness of qualitative analysis (Bergin, 2011). Thus, achieving valid results requires the researcher to remain flexible in using procedures and constantly re-examine the interpretations compared to

the primary data (Kitto, Chesters, & Grbich, 2008). Therefore, the process of data analysis in the present study is adopted from (Elo & Kyngäs, 2008) as follows:

1. 18 Interviews transcripts from audio files into text documents, then analysed using NVivo, Version 12.
2. The transcripts were read and investigated individually, with unique serial numbers, then collectively, without unwarranted assumptions.
3. The individual characteristics of each participant (e.g., current position, educational background, age, gender), the key constructs question regarding the UTAUT (Unified Theory of Acceptance and Use of Technology) model and the six contextual acceptancy predictors obtained from the interviews were analysed in an iterative process.
4. The interview results were used to support and confirm the quantitative research data. The findings from these approaches are elaborated on within the specific sections.

4.7 Results of Phase One Analysis

4.7.1 Introduction

This section reports on the results collected from the semi-structured interview data gathered from a purposive sample of AOD practitioners who have worked in the field of SUD treatment for at least one year in Australia. It explores when, how, to what extent, and for what purpose treatment providers consider digital health in their clinical practice. The outcomes are examined in the context of real engagement and use of digital health with everyday clients in contemporary SUD treatments. It draws upon interviews with 18 Australian treatment providers, extending from AOD clinicians in private clinics to lived experience specialist leaders in therapeutic communities.

It can be argued that digital health technology, whilst shown to be strategically used in certain circumstances, may also, at times, be inappropriate for client needs within clinical work. Therefore, this study investigates the impact of digital health adoption on SUD treatment. The sampling procedure that was carried out and the interviewees' general demographic characteristics will be presented in the first part of this section. The second portion will report on the analysis of the interviews in detail.

As summarised in the methodology section, themes were progressed through deductive coding and pre-defined variables and constructs generated from the UTAUT theory and the SUD contextual acceptance predictors. The twelve key themes (performance expectancy, effort expectancy, social influence, facilitating conditions, trust in technology, clinician's digital health literacy and experience, appropriateness for SUD clients' needs and resources, geographical location, fear of COVID-19, and the possibility of establishing a therapeutic alliance) will be reported sequentially.

4.7.2 Recruitment Process and Demographic Characteristics of Respondents

Recruitment of AOD workers to participate in an in-depth qualitative interview began in September 2021. To distribute our study and approach potential participants, customised email invitations with Qualtrics links were created. Qualtrics "experience management software" provided an effective and convenient way to inform participants of the research aims and objectives. The advice of consent and availability for the interview was provided via direct email, LinkedIn message or text message at the interviewees' convenience (Arechar, Gächter, & Molleman, 2018). The study was conducted in Adelaide, South Australia.

The mean interview length was 40 minutes (ranging from 30 to 50 minutes), and one interview was conducted face-to-face on-site at the treatment providers' location of employment, five interviews were conducted using a virtual meeting platform, and twelve interviews were conducted over the phone. With the permission of the interviewees, a digital recorder was

employed to record the interviews. The recording provided backup to notes taken during the interviews and ensured the accuracy of anything taken down verbatim.

Prior to the actual interview and agreement to participate in the study, each participant was reminded of the research aims and objectives, clarified consent and advised that the interview would be recorded as agreed. In addition, they were advised that they would receive a summary of the findings after the study.

In total, eighteen interviews were conducted between October and December 2021 with treatment providers working at two public treatment services, ten NGOs and three private agencies in Australia (participant details are summarised in Table 7. The eighteen participants included social workers, psychologists, counsellors, caseworkers, and others employed in addiction treatment services. They comprised seven men and eleven women aged 26 to 55 years. Participants' educational and training backgrounds appear relevant to the substance field, although one of the participants has a Diploma in Marketing and Communication.

Table 7 Summary of Demographic Information of Interview Participants (n=18)

Participant	Recruitment Site/Agency	Position/Role	Location	Age	Gender	Education Level	Type of Agency
P1	Life Without Barriers	Case Worker	Adelaide South, Australia	32	Female	Master of Social Work	NGO
P2	Aboriginal Drug and Alcohol Council	Project Officer/AOD Counsellor	Woomera, South Australia	55	Male	Master of Indigenous Health	NGO
P3	Uniting Communities	AOD Counsellor	Adelaide, South Australia	45	Male	Master of Counselling	NGO
P4	Uniting Communities	Case Worker	Adelaide, South Australia	45	Male	Certificate IV in Community Services	NGO
P5	Uniting Church	AOD Counsellor	Canberra, ACT	28	Female	Master of Counselling	NGO
P6	Task Force Community Agency	AOD Clinician/Counsellor	Melbourne, Victoria	26	Male	Master of Psychology	NGO
P7	Thrive Within Counselling – Service	Integrated Psychotherapist-Allied Health Manager-Psychologist	Adelaide, South Australia	55	Female	Master of Clinical Physiotherapy	Private
P8	Uniting Vic.Tas	Lived Experience Specialist Leader	Melbourne, Victoria	33	Female	Diploma in Marketing and Communication	NGO
P9	Assure Mental Health Organisations	Psychologist	Adelaide, South Australia	38	Female	Master of Psychology	Private

P10	Life Without Barriers	AOD Counsellor	Sydney, NSW	42	Female	Bachelor of Counselling and Phytotherapy	NGO
P11	Addiction Coaching Australia	AOD Counsellor	Melbourne, Victoria	38	Male	Diploma in Mental Health Care	Private
P12	Colac Area Health	AOD Clinician/Care Coordinator for Recovery	Colac, Victoria	40	Female	Bachelor of Mental Health	Governmental
P13	Self Help Addiction Resource Centre (SHARC)	AOD Program Coordinator	Carnegie, Victoria	35	Male	Bachelor of Social Work	NGO
P14	Family Drug Support	Family Support Officer/Family Therapist	Adelaide, South Australia	45	Female	Bachelor of Counselling	NGO
P15	The Salvation Army	AOD Practitioner	Canley Vale, NSW	50	Female	Diploma in Community Services	NGO
P16	Drug & Alcohol Services South Australia	AOD Practitioner Psychologist	Adelaide, South Australia	32	Female	Master of Social Work	Governmental
P17	Drug & Alcohol Services South Australia	AOD Practitioner	Adelaide, South Australia	45	Male	Master of Psychology	Governmental
P18	The Salvation Army	AOD Practitioner Psychologist	Melbourne, Victoria	30	Female	Master of Social Work	

4.7.3 Analysis of Interviews- UTAUT Constructs

The 16 questions in the interview schedule designed for this study appeared adequate to answer the research questions. The conversation with the clinicians concentrated on the primary purpose of the research and was guided by the interview guide stemming from themes in the literature and UTAUT factors. Each concept was defined (see Appendix B) and characterised by the appropriate statements, and if the statement did not arise or was not appropriate for the substance field, has been excluded them. The analysis of the main points is discussed below.

1- Performance Expectancy

Following the UTAUT theory, the construct of performance expectancy is represented by statements such as (1) “I would find the digital health technology use in my job”; (2) “Using digital health technology enables me to do my job more quickly”; (3) “Using digital health technology increases my productivity”; and (4) “If I use digital health technology, I will increase my chances of getting a raise.”

Based on the content analysis of the information collected, the most related categories to the above statements that support this construct are the ones that are relevant to the general values associated with digital health technology use. The main two benefits mentioned by the respondents were providing a new and straightforward way of connections for particular groups of clients (For example, clients without a car, single mothers, or clients with social anxiety) (mentioned by 14 people or 77%) and strengthening existing connections (mentioned by 4 people or 22%).

“Sometimes, they are 200k away from the nearest treatment clinic. Also, they have after-hours and weekend access. I made myself available from 8 am to 8 pm, during the weekends for people who work remotely and full time” (Clinician#7)

“Often, clients have social anxiety or other challenges that they cannot attend their regular meetings. To ensure that they have their counselling session and work through their goal and consistency, phone or text or Zoom is good.” (Clinician #15)

However, since the individual usefulness perception of digital technology is highly subjective because of people's pre-judged perceptions (Osubor & Chiemeke, 2015) , clinicians were asked to determine what makes them think digital health is beneficial. Some clinicians reported the client's safety and continuity of care, as well as the ability to provide client-centred care and be responsive to the health status. Some others found it helpful for text message reminders and service efficiency. All interviewees agreed that using e-tools will allow all clinicians and clients to accomplish their requirements during the treatment process faster and more efficiently than traditional approaches. In addition, they commented on the considerable value of adapting new ICT to facilitate real-time communication with clients during the COVID lockdown.

"They could talk to me in their care and away from their family members. Their confidentiality was respected. As we know, a lot of time, the family members of people with SUD problems do not know, and clients want to keep it private. It gives people autonomy to be able to talk to me in a confidential space." (Clinician# 6)

This is not very surprising as these benefits, "Continuum of Care Services "is commonly associated with technology use among other groups of clients as well (Balakrishnan, Gopichandran, Chaturvedi, Chatterjee, Mahapatra, & Chaudhuri, 2016)

2- Effort Expectancy

The following statements characterise this concept: (1) "My interaction with digital health would be clear and understandable", (2) "It would be easy for me to become skilful at using digital health", (3) "I would find digital health easy to use." and (4) "Learning to work using digital health is easy for me" (Mensah, Zeng, & Mwakapesa, 2022).

Nevertheless, as the above statements are very similar and it is an interview data, this research will evaluate four statements together collectively, aiming on interview statements about ease of use, clarity, and learnability of digital tools. Most of the participants identified that Zoom or Microsoft Teams have an easy-to-navigate interface; however, they believed that there is a

learning curve associated with the use of various digital health tools. Remarkably, eight clinicians revealed that most of the issues were not related to the actual learning of how to use the e-tool but had more to do with keeping up with the constantly changing features, latest updates and functionalities. As stated by clinicians,

"it's like anything else; the more you do it, the faster you get at it" (Clinician# 1)

The majority of clinicians indicated that it was much easier to use technology for their internal work-related activities with their colleagues and managers rather than with clients. They indicated that the use of ICT for practitioners who are not technologically savvy will increase their time-consuming documentation and already high work stress and drive them to abandon looking for necessary information and training.

"…We use Zoom quite often to contact our program manager and case conference as they are in another city." (Clinician# 8)

"…some of the applications, it's like an extra thing to do, then I won't do it" (Clinician# 17)

Consequently, "effort expectancy" impacts what digital tools the clinicians in the study chose to use and how they apply them. Although the learnability of e-tools was a lesser problem for this group, the participants mentioned concerns regarding the lack of training and difficulties in using some of the digital tools with colleagues or clients who were not tech-savvy, with challenges magnified due to their high-stress profession.

3- Facilitating Conditions

Subsequent the UTAUT model, the "facilitating conditions" construct is categorised by four statements: (1) "I have the resources necessary "skills training" to practise the digital health technologies"; (2) "I have the knowledge necessary (knowledge and information about the available digital health technology for SUD) to use digital health"; (3) " Digital health is not

compatible with other approaches I use"; and (4) "A specific person (IT support) is accessible to support with technical system difficulties".

The importance of training was frequently emphasised during the interviews. More than half of the interviewees (14 people or 61%) said that they did not have training regarding digital health technology, and the rest had limited training. Because training programs are frequently problem-centred and address the immediate relevance to job performance, people receiving training are more likely to find digital technology easier to use and are more likely to rise their perception of its practicality than those who did not take training (Marshall, Mills, & Olsen, 2008). Apart from a few mindfulness and meditation-related mobile applications, participants had limited knowledge or adequate information about the available technology for SUD treatment.

"…No, I never had any training about using any technology. Is there any? I was involved in some workshops in my previous advisory group, but it was limited to a different setting." (Clinician# 2)

"…In my degree, there was clinical training about text-based counselling: no clinical technology-based intervention." (Clinician# 6)

The lack of IT technical support (hotline, help desk) was only presented by two participants in the study, suggesting that this might be less of a challenge when clinicians are deciding to adopt e-tools for their professional work. However, clinicians in rural geographical locations reported technical or infrastructure challenges such as unstable internet connection and speed, outdated devices, and the network. They indicated that these barriers would influence members' experience with digital health systems, affect their attitude and satisfaction, and slow down the adoption of digital health.

"…the computer that I am on now is a work computer, and I don't think it has a very good WIFI technology. It is slow and annoying. I should go upstairs to be closer to the modem, or I have to hotspot my phone and use the data from my phone. Even then, it is still an unstable internet." (Clinician# 17)

"…. My internet speed drops out in group meetings. Sometimes my computer did not connect to the organisation's network, and I could not access the client's file." (Clinician# 5)

Thus, based on our participants, the study anticipates that "facilitating conditions" such as training and IT support will positively affect an AOD practitioner's decision to use digital health technology.

4- Social Influence

Whilst assessing the "social influence" construct, Venkatesh et al. (2003) applied reports such as (1) "People who influence my behaviour think that I should use digital health technology"; (2) "People who are important to me think that I should practice digital health technology"; (3) "My manager and supervisors encouraged me to use of the digital health technology"; and (4) "In general, the organisation has supported the use of digital health technology".

Based on the transcriptions' analysis, "social influence" undoubtedly performs a crucial role in practitioners' use of digital health. When describing why they started employing a digital tool, many participants referred to circumstances when their manager and other colleagues recommended a tool.

"...We have a regular team meeting on Zoom, and we have to be available online… There is much pressure, so I think many organisations and staff are starting to feel that face-to-face is not enough. It was part of my contract to be available for online counselling" (Clinician# 12)

"One of my old colleagues pressured me to use Teams instead of Zoom for group meetings. I created a Zoom account as many others do and then understood that this was not suitable for the group I am working with now…. for me, so I really am not using it actively." (Clinician# 8)

"…Sometimes I google to see what is available" (Clinician# 15)

Overall, the study observes that "social influence" does show a positive role in practitioners' intention to use digital health, but it does not essentially come from within their current organisation. Colleagues may suggest it via the internet within or outside the same discipline or

field. Furthermore, social influence may encourage people to start via an e-tool, but the person does not need to remain with the initial e-tool. It may depend on the practicality and appropriateness of the tool for particular situations.

the study found that using the Unified Theory of Acceptance and Use of Technology (UTAUT) was really helpful for understanding why clinicians decide to use or not use digital health technologies. Our findings showed that when clinicians believe digital health tools will help them do their job better, known as 'performance expectancy', they're more likely to use these technologies. Specifically, the clinicians participated in this study liked how these digital tools made it easier and quicker to connect with their patients, which was especially important because of the limitations caused by COVID-19.

4.7.4 Extending the UTAUT model: Towards a model for driving digital health adoption in SUD.

This section outlines the initial findings from the qualitative research conducted to refine the conceptual framework that was developed based on the literature review. In addition to the well-established constructs of UTAUT, the study derived six additional hypotheses, characterised by the appropriate statements, from the literature and their influence on one of the behavioural intentions of AOD workers professionals.

This methodological approach enabled us to enhance the UTAUT model by incorporating the following variables: trust in technology, clinician's self-efficacy, fear of COVID-19, geographical location/remoteness, appropriateness for SUD clients' needs and resources and the possibility of establishing a therapeutic alliance. In this sense, and to ensure the study's rigour, the study examined and included variables that were found to be significant in more than 50% of the cases in our final model.

5- Trust in Technology

Based on the literature review and the proposed framework, the construct of trust is represented by statements such as (1) “I have a high-quality network in my workplace”; (2) “there is weakness in the platform and software that I am using”; (3) “there is a technical issue in the platform that I am using”. Almost all participants agreed that the main reason for not using or limiting digital health use could be technical challenges such as unreliable internet connection, speed, devices, and unstable networks.

“We have too many devices and people working in my organisation. Some days, we have a slow connection due to Internet congestion. The IT man cannot do anything about it” (Clinician# 18)

“…Some of our computers are old or damaged; the software needs to be upgraded to the new versions” (Clinician# 2)

Thus, the findings prove that practitioners will have a positive attitude towards digital health when excellent infrastructure is in place and be ready to use it daily. So, the qualitative research confirmed the need to address limited or no technical errors when applying e-tools.

6- Privacy Concern

Apart from technical challenges, concern about privacy was a theme in which emerged from the interviews (15/18). When researcher asked about trust in technology, many interviewees indicated clearly that client’s privacy is one of the key factors in the progress towards the adoption of digital health services. In fact, many clients with substance use disorders are involved in the criminal justice system, drug-related offences, and custody battles (Bennett, Maton, & Kervin, 2008).

“Not only me, but some of my clients are concerned about their personal information. As soon as I call them on Teams, they ask me, are you recording this video? Is there any other person who can hear us?” (Clinician# 11)

“Some of my clients have been in and out of prison; they are too anxious to share their personal information over the phone or on zoom” (Clinician# 9)

“Zoom and Teams are fine for me, but one of my clients stopped the zoom meeting because, in the past, her email and Facebook accounts have been hacked by strangers; they use her personal information and her photo. She is not feeling comfortable talking on online platforms and wanted me to call her instead?” (Clinician#3)

Although privacy was a lesser issue for the clinicians themselves, the importance of the client’s engagement in substance treatment may encourage AOD clinicians to use e-tools. Consequently,” trust” and “privacy” impact what digital tools the clinicians in the study chose to use and how they apply them.

7- Clinicians’ Self-Efficacy

In this study, technological self-efficacy is characterised as clinicians’ assessments of their effectiveness or capabilities to utilise digital tools. The continually growing number of available e-tools and applications and how clinicians see themselves cope with the challenges is identified by statements such as (1) “I’ve already made myself familiar with digital health technology relevant to my practice” (2) “I’ve already made myself familiar with how to download a software in my computer” (3) “I can guide my clients to troubleshoot and fix the issues”. However, not many clinicians believe that they would be able to fix the issues immediately, and they need time or extra resources to be able to handle the situation.

“…I asked my colleague to stay around for the first 10 minutes of my video consultation with my clients in case something happened” (Clinician# 6)

“It is hard to guide clients over the phone to install the Microsoft Teams on their laptops or smartphones. I provided a written step by step guide but still, some of them cannot figure it out” (Clinician# 17)

The interviews data also reflected that technological self-efficacy significantly affects clinicians’ preferences to use e-tools and their perceptions of the usefulness of engaging in a digital health-related task for SUD treatment.

8- Fear of COVID-19

The preliminary interviews confirmed the importance of fear of COVID-19 in the use and acceptance of digital health. Statements such as (1) COVID-19 affected my work? (2) I have concerns about interacting face-to-face with my clients, given the risk of contracting COVID-19 (3) researcher could not see clients because COVID-19. Almost all interviewees express the direct influence of COVID-19 and their use and acceptance of digital technology.

“I can easily see the COVID-19-driven digital acceleration in our organisation.” (Clinician# 18)

“In some stage last year, Zoom and Teams was the only way we could connect to our clients…… I am not sure about the after COVID-19time, but personally, I prefer face-to-face interaction with my clients.” (Clinician# 11)

“The blended treatment approach is my preference for the post-pandemic world.” (Clinician# 8)

From the interview responses, it was evident that COVID-19 accelerated the adoption of digital technologies and virtual communication tools. Like the other disciplines such as technology and science (Paunov & Planes-Satorra, 2021), public health (Vargo, Zhu, Benwell, & Yan, 2021) has moved considerably toward online channels; interacting with clients was only possible through digital health technology at various stages during the pandemic. The interviews proved that responses to COVID-19 have accelerated the adoption of digital technologies.

9- Geographical location/Remoteness

The unbalanced distribution of health workers among and within countries is a global problem. All nations report a higher percentage of health employees in urban and wealthier localities (WHO,2002). The majority of participants identified (16/18) clear benefits of digital health for clients living in rural communities with a long distance from primary services. However, they also emphasised the digital exclusion such as network extension, lack of infrastructure and the lower level of public services.

"I worked a lot with the remote community; drug and alcohol services are limited with the long waiting list." (Clinician# 3)

"… there is only another social worker in this town and me. We could see more clients over the phone or on Zoom compared to face-to-face meetings. Some of my clients live in a pretty remote area. The NBN company will send a technician to their house as it will likely require a round trip of maybe 600 km - and install a satellite earth station on their roof and other pieces of equipment". (Clinician# 10)

On the other hand, the clinicians from the big city and densely populated areas stated that the costs of laying the infrastructure and providing services are lower due to economies of scale and a reliable internet connection is available. However, due to the service availability, clients prefer face-to-face meetings rather than virtual support. So, the interview data expressed a difference between the use of digital health in different locations and service accessibility considered necessary due to multiple justifications.

10- Client E-Literacy and Access

The degree to which clinicians can engage with clients digitally also depends on the situation, digital skills, and clients' resources. Engagement with clients will be lower if they suffer from mental issues, have low levels of education, are unemployed, are in low-income households, and/or living in rural or remote areas, which are more likely to have low internet literacy,

unreliable internet access, and not owning a smartphone, according to the interview results. The following statements characterised these contracts: (1) “my clients do not have the resources for online interaction (internet connection, smart devices)”, (2) “my clients would find digital health is a practical option to use.” and (3) “learning to work using digital health is easy for my clients and me.” Most of the clinicians identified that their clients are fine using Zoom or Microsoft; however, many have issues finding digital solutions for their technical problems.

“How can I video-call my clients when the internet drops out every 10 seconds? Around 30% of my clients live in a remote area, and the internet access is so bad almost every day. …… they are fine, but …if something happens, they get stuck and cannot solve the problem.” (Clinician# 2)

“Some of my clients, living in shared accommodation, and they do not have a private area to be able to talk to me? ……it is widespread among my clients to sell their smartphone or their computer for drugs…...” (Clinician# 13)

So, clients’ digital skills and literacy resources influence what digital tools the clinicians in the study chose to use and how they apply them. However, some clinicians showed concerns when their clients’ technical ability and resources, especially those with long and severe histories of substance dependency and other mental health issues. The interviewees stressed the necessity to include clients in any training programs and spread awareness of digital health use and adaptation.

11- The Possibility of Establishing a Therapeutic Alliance/ virtual intimacy

The importance of the client’s interaction in the treatment process was frequently emphasised during the interviews (#17 and #18) as it can be a variable in explaining the successful treatment outcomes. Similar to conventional clinician-delivered interventions, the working alliance (also known as the therapeutic alliance) can consistently be one of the primary predictors of clinicians' acceptance and use of technology.

The following statements characterised these contracts: (1) “I believe my clients can achieve their treatment goals with digital health technology)”, (2) “I believe my clients can do their treatment task with digital health technology) (3)-“I have the same relationship with my clients in an online environment.” Most of the clinicians identified that their clients could achieve their goals and follow their tasks by using an online platform such as zoom and Teams. However, when asked how the clinicians feel about their relationship with their clients in an online environment, most of them, Clinicians #15-18, emphasised the lack of virtual connection with their clients.

“I found it very challenging to build rapport as quietly as I would be able to do it in the room, face to face situation.” (Clinician# 13)

“I prefer to see them face-to-face. As they are in residential rehab treatment, seeing them face-to-face can help me absorb their behaviour. How they are talking and walking, their body language and …. Then we can do a urine test and check whether they used substance again or not.” (Clinician# 13)

“Human beings do not like to be alone. It is in our DNA and our subconscious. We are not supposed to be alone. The lockdown was difficult for many people. It triggered a lot of mental issues for many people.” (Clinician# 13)

Due to the nature of the substance treatment, the majority of the clinicians (#15 - #18) still preferred the hybrid style of the interaction. The development of the therapeutical alliance may not be possible and affect the treatment outcome.

4.8 Limitations

The interviews were carried out with clinicians who had familiarity and understanding of digital health technologies in Substance Use Disorder (SUD) treatment environments, yet their experience levels with these technologies differed. Consequently, some participants were unable

to provide detailed feedback on specific technological features. Nonetheless, incorporating clinicians with a wide range of e-health experiences in SUD care enhances the scope of our study and reflects the varied levels of digital health technology exposure that users encounter in real-world settings.

4.9 Conclusion

The outcomes support previous research on technology adoption in SUD treatment settings. Digital health technologies have the potential to improve access to and improve the quality of substance care, particularly during the COVID-19 lockdown. Our results demonstrate that digital health technologies designed to address the particular problems of substance use treatment delivery (e.g., poor client access disparities in the service's availability, insufficient treatment knowledge) are viewed as the most valuable among the providers.

However, the ease of applying such technologies influences clinicians' intention to use and adopt them. Additional participants' strong consideration of clients' resources and digital skills, clients' privacy, and lack of virtual intimacy and therapeutical alliance in the online environment were some of the key points of the interviews. All questions in the interview were effectively answered, adding more detail, not only about the e-tools but also about clients' needs and engagement. This profusion of data enriched a qualitative analysis of e-health, which was concluded by deriving ten core variables, one of which emerged from the interview, which was analysed and reported. Although the requirements and circumstances of SUD treatment differ among individuals and regions, the insights from this research serve as an essential foundation for guiding the adoption of digital tools to facilitate the growth of SUD treatment services. The push towards digitalisation, hastened by the COVID-19 response, is expected to remain a continuous practice within SUD treatment frameworks moving forward, given the pandemic's probable enduring influence on healthcare access methods. In the subsequent chapter, the qualitatively report, analyse, and synthesise the conceptual model will be reported to unveil and discuss the study's ultimate conclusion.

5.0. CHAPTER FIVE – METHODOLOGY-TESTING OF MODEL

5.1. Overview

Given the recognition of a mixed-method approach in developing and examining conceptual models, this study combines qualitative and quantitative methods. Chapter 4 discussed a qualitative approach to exploring clinicians' views on digital health in SUD treatment settings. This chapter will explain the subsequent quantitative approach, investigating which digital health tools, how many, how often they are used, and to what extent digital health applies to SUD's everyday practice in Australia.

This section delves into the methodology employed for gathering data, including the design of the questionnaire, the scale and measurement used, the drafting of the questionnaire, pre-testing, and the approaches taken to mitigate or eliminate potential flaws. In particular, this chapter highlights and provides the rationale for 1) defining and operationalising the constructs, 2) creating the measurement scale, 3) drafting the initial version of the instrument, and 4) ensuring the instrument's validity and conducting a pre-test to gather accurate and comprehensive information relevant to the research questions.

5.2 Data Collection Method

A quantitative survey is used to test theoretical models empirically. Surveys involve "collecting information from a sample of individuals through their responses to questions" (Check & Schutt, 2011, p. 160). This method allows the researcher to recruit participants, accumulate data, and employ various instrumentation methods, and as it is frequently used to explain and investigate people's behaviour, it is commonly applied in psychological and social science disciplines. Additionally, quantification enhances the structure and transparency of the study in terms of the method of data gathering and analysis that can be repeated and followed by other scholars (Check & Schutt, 2011).

Finally, given the lack of research on the intersection between digital health and substance dependency treatment, the variables and conceptual framework proposed in this study will significantly contribute to substance use disorder treatment and human-technology disciplines. Furthermore, due to its replicable nature, the questionnaire survey can be adapted for use in different fields, providing an opportunity for methodological comparison and the ability to verify its reliability when reproduced (Avgousti, 2013).

It is also crucial for the researcher to understand the potential for bias in survey research and the tested strategies for lowering bias to draw appropriate conclusions. Summarised in Table 8 are the common types of error in the study, the causes of error and tactics to address the limitations of the survey.

Table 8 Source and Limitations of the Survey Research and the Technique Used to Reduce or Cover the Error

Type of error	Source of error	Strategies for reducing the error
Coverage error	Some people in the population might not get a chance at all to take part in the study.	Multimode design
Sampling error	The people in the study do not accurately reflect the broader population's traits.	Clearly define the population of interest.
Measurement error	The questions do not get honest responses and do not really capture what the topic is about.	Check the validity and reliability of the instrument. Pre-test questionnaire. Use sensible wording
Nonresponse error	Not everyone in the sample responded.	Follow-up procedures for non-respondents- well-constructed survey design
Adopted from: (Check & Schutt, 2011; Dillman, Smyth, & Christian, 2014; Singleton, Straits, Straits, & McAlister, 1999)		

The survey method was selected for two key reasons in the current research. Firstly, the study is limited to exploring the factors shaping the use and adoption of digital health in SUD treatment settings in Australia. Secondly, a survey is appropriate as this study aim to measure clinicians' attitudes and intentions to use digital health in SUD settings. Hence, the survey is suitable for collecting original data describing a larger population geographically dispersed across Australia.

Thus, in this study, the questionnaire was employed to determine the extent of the impact of factors on the use and acceptance of digital health in the SUD field in Australia by utilising the extended UTAUT model. A questionnaire is one of the most commonly held data collection tools and is considered one of the best options for many participants in a time-sensitive manner (Gray & Gray, 2009). Furthermore, a high-quality questionnaire with two main attributes, clarity and capturing participants' perspectives, can provide high validity and reliable measurement for the researchers and facilitate easy understanding and appropriate responses from participants (S. H. Lee, 2006).To develop a draft questionnaire, the researcher follows the subsequent practical procedures, including using precise wording and language, selecting the sample, and generating a good cover letter (Leedy & Ormrod, 1993).

Based on a comprehensive literature review of UTAUT studies, each construct was added to the conceptual model, which was validated by conducting 18 qualitative in-depth interviews. The researcher could then develop and design a questionnaire instrument. The questionnaire was pre-tested and refined before being distributed for data collection. In brief, the questionnaire data collection procedure is achieved in these two steps.

1. Creating and developing the questionnaire.
2. Testing the questionnaire beforehand and then making changes to it.

5.3 Questionnaire Design

5.3.1 Scales and Measurement

As stated in the previous section, this study used the survey method to investigate clinicians' intentions and attitudes. Consequently, the attitude scale was used to measure the participants' attitudes towards specified subjects and questions on the attitude scale were formulated so that the study participants could agree, disagree or be neutral with them. Also, attitude scales can measure and predict beliefs and behavioural intentions (A. Lewis, 1994)

Likert scales are among the most popular methods of attitude scaling (Bryman, Becker, & Sempik, 2008). In this research, every construct within the questionnaire is measured using a multi-item, 7-point Likert scale. This asks clinicians to express their views by rating them from "strongly agree" to "strongly disagree."

In addition, nominal scales, which generally assign numerical values to categories or codes and present the lowest levels of measurement (Ghauri & Grønhaug, 2005), have been used to control variables such as the nature of the treatment provider's agency and the clinicians' location. The scale was chosen for its ability to clearly delineate responses from strongly positive to strongly negative, offering deep insights into participants' attitudes with a neutral midpoint (Bowling, 2002).

The 5-point Likert scale allows participants to easily review all scale descriptors, unlike the longer seven-point scale, and is the most commonly used in e-health adoption and UTAUT-related research (Alshammari, Alshammari, & Alshammry, 2021; Elahi, Liang, Malik, Dilawar, & Ilyas, 2021; Putteeraj, Bhungee, Somanah, & Moty, 2022; Siebert et al., 2022).

Nevertheless, the Likert scale has some shortcomings. For example, it may not be able to measure all opinions, and some participants might default to neutral evaluation or choose the same responses to a sequence of questions without genuinely thinking about them (A. Lewis, 1994). Thus, for all items, the questionnaire was arranged on a five-point Likert scale ranging from 1= strongly disagree to 5= strongly agree.

5.3.2. Drafting of Questionnaire and Pre-Test

An optimal questionnaire should be valid, reliable, transparent, succinct, and engaging. In other words, participants should clearly understand the research objectives, produce the same answer promptly if presented repeatedly and follow the logical sequence with the appropriate administration procedure (Jenn, 2006). In addition, further attention was given to each question's wording, content, and structure. Vocabulary was appropriate by avoiding jargon, vagueness,

double-barrelled questions, leading or biased questions, and simple, straightforward language (Ticehurst & Veal, 2000). Questions were organised logically, with groupings between related items and logical sequencing of constructs.

The questions had a clear structure, utilising two types of questions. Open-ended questions were employed to gather information on variables such as years of experience and geographical location. Multiple-choice questions were utilised for demographic characteristics. Scale questions were applied to the other sections of the instrument. Appendix ---includes a copy of the questionnaire used primarily in the pilot study. The questionnaire comprises 56 demographics and digital health state questions or statement items to evaluate 14 constructs of interest.

The UTAUT model is composed of five constructs: Performance Expectancy (4 items), Effort Expectancy (4 items), Social Influence (4 items), Facilitating Conditions (4 items), and Behavioral Intention (3 items), as detailed in Table 9. The questionnaire also included 17 closed-ended questions representing the respondents' demographic characteristics. Each construct has around 4 or 5 items detailed in Table 9.

It is highly recommended to pre-test the study questionnaire to ensure that each item is clear and understandable to an average participant (Sekaran & Bougie, 2003).Pre-testing can also reduce sources of measurement error and achieve content validity and reliability. (Hair, Black, Babin, Anderson, & Tatham, 2006). To assist the study in attaining appropriate responses. Practically, a pre-test can '(1) determine ways to surge participant interest, (2) encourage the probability for participants' engagement, (3) identify errors and problems, (4) identify challenging questions and areas where investigator supervision may be required, and (5) identify ways to enhance the overall quality of the study data'(Cooper, Schindler, Cooper, & Schindler, 2006, p. 385). Hence, the expert review technique was applied during the questionnaire pre-test in this research as detailed in the following part.

5.3.3 Validity of the Pre-Tested Preliminary Research Instrument

Different procedures were employed to verify the validity of the research instrument. Primarily, the questions formulated for measuring each variable were established on validated items from previous research (Venkatesh & Davis, 2000; Venkatesh et al., 2003). In addition, the questions were reworded and adapted to suit the current study aims, objectives and context.

The researcher distributed the questionnaire to three supervisors and five PhD students with deep expertise in digital health and Substance Use Disorder (SUD) treatment in Australia, asking them to review, respond, and offer feedback. Based on expert suggestions, adjustments in phrasing and the sequence of certain questions were made. Following these revisions, the final survey questionnaire was presented and approved. Subsequently, the questionnaires were disseminated among a diverse group of Alcohol and Other Drug (AOD) workers across Australia.

5.3.4 Sampling

Sampling strategies in quantitative analysis aim to find an adequate sample representative of the population of interest. A substantial targeted and random section enhances the probability that the answers from the individual participants will genuinely reflect the entire population. As it might not be possible to accumulate data from an entire population of interest (e.g., all AOD clinicians in Australia), a subgroup of the people or sample is employed to assess the participant's responses to draw valid conclusions (Ponto, 2015). It is, therefore, necessary to correctly identify the population of interest of this study (e.g., AOD clinicians who have worked in any SUD treatment setting in Australia for at least one year and are currently in direct relationship with clients' vs all AOD clinicians).

Simple random sampling is the purest type of probability sampling. With this method, individuals are chosen randomly. Simple random sampling can be an appropriate option to provide each member of the study population an equal opportunity to be selected as the subject (Olken & Rotem, 1986).

The question of sample size is essential because using larger samples can intensify the detection of differences, highlighting statistical differences that are not relevant. Conversely, smaller samples may prevent the findings from being extrapolated and transferable (Altman, 1990). Therefore, to gain as much information as possible from AOD clinicians, the researcher distributed the study questionnaire among a relatively large sample; a minimum of 100 AOD clinicians is the target for this study.

5.3.5 Data Collection Strategy

Conducting face-to-face or telephone interviews with a relatively large number of AOD clinicians in Australia would not be time-efficient, economical, or practical. So, this research will use the online survey as its data collection method to clarify unclear survey responses or reduce the potential for measurement and nonresponse error. The researcher might do a follow-up phone call or email as suggested and follow the mixed methods survey research approach, which can help to ensure better sample coverage (Dillman, Smyth, & Christian, 2014; Dixon, Singleton, & Straits, 2016). Online surveys have exploded in recent decades as they raise productivity by saving time; data is instantly accessible and can easily be transferred into spreadsheets or specialised statistical software when detailed analysis is required. Additionally, this study can pilot the research quickly and adjust and strengthen the survey designs (Coppock & McClellan, 2019).

Similar to the qualitative phase, this research drew its sample from social and professional online social media and networking sites (Hill, Dean, & Murphy, 2013) by employing simple random sampling techniques. Thus, this study used LinkedIn, Facebook, and Twitter applications to optimise the sampling process. Furthermore, since this questionnaire study was established as a web survey, it assisted in accessing the participants from an extensive area.

This study employed an electronic questionnaire by subscribing to Qualtrics http://qualtrics.com to collect data. To boost the response rate, the researchers provided a short email, introduced the purpose of the study, estimated the survey completion time (20 minutes),

and requested participation and the link to the online questionnaire. The data-collection procedure occupied 5 months, beginning on 25 December 2022 and ending on 1 June 2023. A total of 140 responses were received, and 120 were completed and valid for analysis, making the percentage about 85%.

To encourage targeted people to participate in the survey, each participant was registered in a prize draw competition to win a tablet. Additionally, the survey results would be made available to interested respondents.

5.4 Concept and Operationalisation of Construct

Before data collection, a theoretical or conceptual definition is required for each construct of the proposed conceptual model. Conceptualisation is the procedure of defining what is mean when using specific terms or concepts, and operationalisation is the process by which a researcher precisely specifies how a concept will be measured (Bryman, Becker, & Sempik, 2008). The measurement improvement method started with conceptualisation and finished with operationalisation (Middendorp, 1991). Indeed, the constructs should be specific and hypothetically observable. In this research, the previous studies in the relevant field of each construct acted as a guide for developing measures. In other words, theoretical constructs were operationalised using validated items from previous research and explicitly modified to the context of the SUD treatment setting.

5.4.1 UTAUT model constructs

Chapter 3.2 explained the technology acceptance theories and justified why this study used the UTAUT model. In brief, TRA, TAM, TPB, TAM-TPB, MPCU, MM, SCT, and IDT are criticised for their relatively small explanatory ability regarding behavioural intentions, ranging from 30 to 40 percent. This research employed the UTAUT model with its constructs introduced by (Venkatesh et al., 2003), which has high explanatory power, amounting to 70 percent, and is established based on the practical and theoretical resemblances of the

previous eight theories. Furthermore, with some adjustments to reflect the particular behaviour of AOD clinicians, the measurement of the UTAUT constructs is shown in Table 9 in detail. Consequently, these measures were incorporated and tailored to the SUD context.

Table 9 UTAUT Constructs and Relevant Questions.

Performance expectancy (PE): The degree to which an individual believes that using the system will help him to attain gains in job performance	
PE 1	Using digital health enables clinicians to accomplish their duties more quickly and efficiently.
PE 2	Using digital health increases the equity of clinicians' work.
PE 3	Using digital health would help clinicians to save time.
PE 4	Using digital health increases the quality of addiction treatment services.
Effort expectancy (EE): The degree to which an individual believes that ease is associated with the use of the system	
EE 1	Learning to work with digital health is easy.
EE 2	Using digital health is easy.
EE 3	It is easy for me to become skillful at using digital health.
EE 4	By using digital health, I am able to obtain treatment services easily.
Social influence (SI): The degree to which an individual perceives that important others believe he should use the system	
SI 1	People who are important to me think that I should use digital health.
SI 2	People who influence my behaviour think that I should use digital health.
SI 3	I would use digital health if my friends and colleagues used them.
SI 4	In general, I have been supported in the use of digital health.
Facilitating conditions (FC): The degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system	
FC 1	I have the resources necessary to use digital health (WIFI/laptop/computer)
FC 2	I have the knowledge necessary to use digital health (Computer knowledge)
FC 3	I think using digital health fits well with my work/position responsibilities.
FC 4	A specific person (or group) is available for assistance with digital health difficulties (IT support)
Behavioural intention (BI): The degree to which an individual intends to use e-tools (Venkatesh et al., 2003).	
BI 1	I plan to use digital health in the future.
Use Behavior of Digital Health: The actual use behaviour (USE) of a specific system (Ong, Day, Chen, & Hsu, 2008).	

How often do you use the following digital health technologies?

Digital health *includes a range of technologies, such as video counselling, mobile apps, website, email, and wearable devices, that can support you or your clients for training, communications, referrals, assessment, or any other work/treatment-related activities.*

	never	Rarely	Sometimes	Often	Always
1-The phone call/ Email					
2- Mobile App related to substance dependency					
3- Video conferences (Skype, Zoom, WhatsApp&….)					
4- My organisation's software					
5-Other (big data, cloud computing, blockchain, and health sensing)					

5.4.2 SUD Constructs

In this research, six new constructs, trust and concerns about privacy, geographic location, clinician's self-efficacy, fear of COVID-19, client E-Literacy and access, and the possibility of establishing a therapeutic alliance /virtual intimacy, have been added, and relevant measures were included. Scale development for the constructs was based on an extensive survey of the relevant literature and valid standard scales used for as much as possible and presented in Table 10.

Trust

As mentioned in Section 3.3.5, the existing technology acceptance literature essentially perceives trust as technical reliability and relates to whether a service will experience systems faults or other failures. However, trust in technology can influence the clinician's beliefs and use of digital technology, and many studies include trust as one of their essential contributions to the acceptance of technology.

Trust is critical in the online world where visual expression and absolute transparency are not present (Benbasat & Wang, 2005). Also, because of the impersonal nature of the Internet, end users should think the organisation delivering the service is reliable, as the lack of trust can be one of the most challenging barriers to e-tool use and acceptance, especially when sensitive personal information or finances are required (Y. D. Wang & Emurian, 2005).

Considering the contexts and trust constructs, the study will use Merritt's trust scale using six Likert-scale items in this study. It can assess clinicians' overall trust and reliance on technology. Also the researcher going to change and adopt the language in the questionnaire as the other studies on attitudes and the use of technology have distinguished that the reliability and validity of measures can be augmented by using language that is more specific for a particular context, which diminishes clinicians' ambiguity and increases the capability to predict behaviours(Frazier, Johnson, & Fainshmidt, 2013; Ryan et al., 2019).

Concern About Privacy

Privacy concerns have been described as fear of the loss, breach, infringement, or violation of confidentiality and the need for safety strategies against unwanted mismanagement and interaction with personal information (H. Jeff Smith, Sandra J. Milberg, & Sandra J. Burke, 1996). In our qualitative phase, clinicians emphasise their concerns about clients' privacy. They highlighted that their clients were anxious about potential unwanted legal and socioeconomic consequences resulting from misusing their personal information. Furthermore, they understand that some of their clients have previously experienced or know somebody who experienced internet blackmail, identity theft, or financial loss due to the impersonal nature of the online environment. In addition, participants in our study stated that since personal information must be disclosed in a SUD treatment service, clients may become reluctant to provide such details for fear of improper data handling. Thus, privacy concerns might affect the information disclosure and treatment outcome.

In this study, privacy concerns were evaluated by five-point Likert scale items that were carried from the measurement of concern for information privacy (CFIP) summarised in (H Jeff Smith, Sandra J Milberg, & Sandra J Burke, 1996), this includes gathering individual data, unauthorised secondary use of personal data, inaccuracies in personal data, and illegal access to personal data. However, the phrasing was subsequently revised and corrected as needed.

Geographic Location

Geographic location is the specific physical point on Earth where the statistical unit (e.g., individual) is located (Erkin & Shakhrizoda, 2022). As explained in Chapter 3, many studies have discovered that people's location influences their approach and willingness to use digital services. For example, individuals living in rural regions have demonstrated a great interest in using digital health services. In contrast, the attraction was lowest among individuals living in metropolitan and capital cities (Bhatia, 2021). Consequently, the clinicians asked to provide their postcodes.

Clinician's Self-Efficacy

In Chapter 4, self-efficacy was justified and could be characterised as confidence and perception of clinicians in their ability to manage and conduct a set of specific actions necessary to achieve performances. In addition, previous research indicates that technology self-efficacy is a significant predictor of effective technology acceptance (Venkatesh & Davis, 2000).

Various scales to measure particular aspects of technology self-efficacy have been established and validated; however, this study used a 10-item scale developed (Compeau & Higgins, 1995) designed primarily for workplace professionals. Modifications were made to the scale items' wording or omitting some similar or irrelevant questions to make it applicable to a population of AOD clinicians.

Fear of COVID-19

The advent of COVID-19 and its pandemic has exacerbated people's fears and anxiety, leading to stigma in some cases (Ahorsu, Lin, Imani, Saffari, Griffiths, & Pakpour, 2022). The impact of external factors such as COVID-19 can influence people's acceptance and use of technology (Khan, Liu, & Rasheed, 2020; Nand, Pitafi, Kanwal, Pitafi, & Rasheed, 2020). In other words, the fear of COVID-19 positively correlates with clinicians adopting digital health services. To measure the fear of COVID-19 this study, applied FCV-19S, which has seven items and was developed by (Ahorsu, Lin, Imani, Saffari, Griffiths, & Pakpour, 2020). In addition, some adjustments were made to the wording and the higher the score, the greater the fear of COVID-19.

Client E-Literacy and Access

To be effective digital health consumers, clients must learn self-management skills and become active contributors to knowledge management and exchange. Digital literacy is regarded as critical to the development of these skills. Digital literacy comprises more than the ability to manage software or use a digital device; it involves a combination of cognitive skills, collaborative skills, social awareness, and practical technology skills (Martin & Madigan, 2006). Therefore, it is

understandable that there is a link between e-health literacy and technology usage in general. The more clients use digital technology, the more likely they will improve their skills in using e-tools. Therefore, in this research, the e-Health Literacy Scale (eHEALS), developed with 8 items, with 8 items has been adopted to measure the clients' combined knowledge, comfort, and perceived skills at finding, evaluating, and applying digital health for their treatment journey.

Despite having relative knowledge of e-Health, many clients cannot derive the full benefit from it. Therefore, access to and affordability of digital health technology for disadvantaged and vulnerable clients is an ongoing concern and understood to be essential for access to services and support networks and services, as well as for attaining decent quality health outcomes (Ahmed et al., 2020; Eyrich-Garg, 2010).

The price of smartphone and Internet services is regularly cited by clinicians participating in the qualitative phase as one of the significant barriers to Internet access and use. They stress that some of their clients experiencing substance dependency find it challenging to maintain the cost of their smartphones and connectivity. For instance, the monthly payment costs for a mobile service or repair must be considered considering clients' overall income, hardship, and substance dependency circumstances. Therefore, this research will use the 2 item questions (Porter & Donthu, 2006) to measure the perceived access barriers for clients.

Possibility of Establishing a Therapeutic Alliance /Virtual Intimacy

Digital health interventions for SUD treatment continue to demonstrate effectiveness for many treatment outcomes. In general, it seems that a therapeutic alliance can be cultivated in digital interventions mediations However, the elements may change in digital environments and may have unique aspects in these contexts. This study used the Agnew Relationship Measure (ARM) scale to measure the therapeutic alliance in the SUD treatment setting. The questions of the therapeutic partnership consist of 3 components: (1) the client-clinician bond and sense of therapist supportiveness (item 1), (2) agreement on the task's direction and therapeutic goals

(items 2 and 3), and (3) clients and clinicians' confidence in the therapy approach (items 4 and 5)(Agnew-Davies, Stiles, Hardy, Barkham, & Shapiro, 1998). In addition, questions were modified and adjusted for better fitness.

Table 10 Scale Adopted

n	**Construct**	**Scale Adopted from**	**Number of items**
1	Trust	Merritt's Trust Scale (Merritt, Heimbaugh, LaChapell, & Lee, 2013)	6
2	Concern About Privacy	CFIP Scale (H Jeff Smith, Sandra J Milberg, & Sandra J Burke, 1996)	5
3	Geographic Location	(Erkin & Shakhrizoda, 2022)	1
4	Clinician's Self-Efficacy	Computer Self–Efficacy (CSE) (Compeau & Higgins, 1995)	10
5	Fear of COVID-19	FCV-19S (Ahorsu et al., 2020)	7
6	Client E-Literacy and Access	e-Health Literacy Scale (e-HEALS) (Norman & Skinner, 2006b) -Perceived Access Barriers for Clients (Porter & Donthu, 2006)	8 2
7	Possibility of Establishing a Therapeutic Alliance /Virtual Intimacy	Agnew Relationship Measure Scale (ARM) (Agnew-Davies et al., 1998)	5

Table 11 SUD Contracts and Relevant Questions.

Trust (TR): to believe that an e-tool, machine, or equipment will not fail (Sheridan, 2002)	
TR1	I usually trust digital health until there is a reason not to.
TR2	For the most part, I distrust digital health.
TR3	In general, I would rely on digital health to assist me.
TR4	My tendency to trust digital health is high.
TR5	It is easy for me to trust digital health to do its job.
TR6	I will likely trust digital health even when I know little about it.
Privacy Concern (PC): "the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others" (Chai et al., 2009)	
PC1	It bothers my clients when I ask them about their personal information.
PC2	Some of my clients are concerned that I will collect too much personal information.
PC3	Some of my clients are concerned that unauthorized people may access their personal information.
PC4	Some of my clients are concerned that my organisation or I may keep their personal information in a non-accurate manner.
PC5	Some of my clients are concerned about submitting their information to websites.
Self-efficacy (SE): is one's belief in one's ability to execute a particular task (V. Venkatesh &Davis, 1996)	
SE1	I could use any new digital health tool if no one were around to tell me what to do.
SE2	I could use any new digital health tool if I could call someone for help if I got stuck.
SE3	I could use any new digital health tool if I had more time to become familiar with it
SE4	I could use any new digital health tool if I had just the built-in help facility
SE5	I could use any new digital health tool if someone showed me how to use it first
Fear of COVID-19(FC19)- The sharp increases in fear and worries relating to the virus (Asmundson & Taylor, 2020a; McCarthy, 2020). Fear is defined as an unpleasant emotional state that is triggered by the perception of threatening stimuli (de Hoog et al., 2008)	
FC19-1	I am very afraid of COVID-19.
FC19-2	It makes me uncomfortable to think about COVID-19.
FC19 3	My hands become clammy when I think about COVID-19.

FC19-4	I am afraid of losing my life because of COVID-19.
FC19-5	I become nervous or anxious when watching news and stories about COVID-19.
FC19-6	I cannot sleep because I am worried about getting COVID-19.
FC19-7	My heart races or palpitates when I think about getting COVID-19.
Digital Literacy (DL): the set of skills needed to find, retrieve, analyse, and use information" ACRL (2007)	
DL 1	My clients know how to find helpful health resources on the Internet.
DL2	My clients know how to use the Internet to answer their health questions.
DL3	My clients know what health resources are available on the Internet.
DL4	My clients know where to find helpful health resources on the Internet.
DL5	My clients know how to use the health information they find on the Internet to help them.
DL6	My clients have the skills they need to evaluate the health resources they find on the Internet.
DL7	My clients can tell high quality from low-quality health resources on the Internet.
DL8	My clients feel confident using information from the Internet to make health decisions.
Digital accessibility Barriers (AB): the extent to which a product, device, service, or environment is available and navigable for persons with special needs or functional limitations (Lazar et al., 2015).	
AB 1	My clients cannot afford to have a smartphone.
AVB 2	My clients do not have the money to get an Internet connection.
Geographic location (GL): specific physical point on Earth. The physical area wherein the statistical unit (e.g., individual) is located (Erkin, G., & Shakhrizoda, H. (2022).	
GL1	What is your postcode? …….
Therapeutic Alliance (TA): the concepts of transference and countertransference, which are the unconscious feelings or emotions that a patient feels towards their therapist, and vice-versa (Freud S., 1912)	
TA 1	My online session is as supportive as my face-to-face session?
TA2	My clients and I agree about how to work together in online sessions.
TA 3	My clients and I have difficulty working jointly in online sessions.
TA4	I am confident in my digital skills in my online therapist sessions with my clients.
TA5	I am confident in my abilities during my online therapist sessions.

5- 5 Face Validity Test and Pertest for the Instrument

This phase comprised conducting a validity assessment. Face validity concerns whether each statement or item created to assess a construct genuinely measures that construct. Bryman (2008) suggests that it is feasible to engage proficient or experienced individuals to serve as assessors to ascertain whether the items on a scale exhibit face validity (Bryman, Becker, & Sempik, 2008). Consequently, the research instrument was subject to scrutiny by three experts in digital health and SUD treatment, along with the evaluation of a consultant specialising in statistics. They were requested to provide input on the ability of the survey questions to precisely assess each construct, their clarity, potential vagueness or ambiguity, and any inconsistencies that might be present in the questions. Based on their comments and recommendations, overlap among some statements was adjusted, and specific questions were revised to enhance their clarity. For example, several of the questions measured the same or similar constructs.

Moreover, the questionnaire was pretested by three PhD students, who were invited to answer the questionnaire and to find out if there were any difficulties with understanding the survey questions or the complex language used in the questions. Finally, all relevant feedback was included into the instrument, which was then ready for use in the pilot study.

5.6 Pilot Study

After the primary research instrument was pre-tested, a quantitative pilot study and a complete field survey were completed. The pilot study is a critical stage in a research project that detects potential issues or shortcomings in the research instruments before implementing them in the full study (Lancaster, Dodd, & Williamson, 2004).

For the scope of the pilot study, ten AOD clinicians with a minimum of one year of experience working in Any SUD treatment agency in Australia were chosen randomly. Participants were invited to comment and give feedback on the instrument regarding unclear ambiguity or wording.

5.7 Ethical Considerations

Ethical considerations are an essential part of any research design (Neuman,2006). In the context of this research, several stages were implemented to ensure that. The requirements of ethical study practice were met. Firstly, the study was approved by the Human Ethics Low-Risk Panel of Flinders University (Approval NO 4656; see Appendix E). Secondly, all participants were advised about the researcher's subject, objectives and aims and how this study will help clients, clinicians, and decision-makers afford more effective and actual services through digital health. Additionally, participants could withdraw at any stage, and the contact details of the researcher and supervisor were provided if participants had any ethical concerns. Finally, participation in the survey was anonymous and voluntary.

5.8 Chapter Summary

Chapter 5 discusses and presents many aspects of quantitative research, including data collection method, questionnaire design, scales and measurement, questionnaire, pre-test, sampling, and data collection strategies. The chapter also explained the justification for selecting the research methods and strategies. The Concept and Operationalisation of Constructs comprising UTAUT model constructs and SUD constructs were introduced, and the relevant questions and measurement scales were presented. Finally, ethical consideration and approval were outline in detail. The next chapter gives the steps and results of the descriptive data analysis.

6.0. CHAPTER SIX: QUANTITATIVE ANALYSIS AND RESULTS

6.1. Overview

This chapter provides an in-depth look at the quantitative analysis conducted for the study, focusing on measuring clinicians' adoption and usage of technology. The initial sections elucidate the results of the descriptive data analysis, which includes statistics on the frequency and percentages related to age, gender, level of education, geographic location, behavioural intention, and user behaviour concerning digital health platforms.

Additionally, the chapter presents essential insights into crucial considerations for data analysis using Structural Equation Modeling (SEM). Before testing our hypotheses through confirmatory factor analysis via SEM, several preparatory steps were undertaken, starting with data preparation and then assessing data normality. The chapter also assesses and reports on the reliability and validity of constructs comprised of multiple items. While the results are outlined and briefly scrutinised within this chapter, a more comprehensive discussion of the findings will be presented in section 6.5. A summary of this chapter is provided in Section 6.6.

6.2 Descriptive Analysis

In this study, a total of 200 questionnaires were initially distributed. A response rate of 70% was achieved, yielding 140 completed surveys. However, not all these responses could be included in the final analysis. Due to missing essential factors, lack of completion, or responses from individuals who were not AOD practitioners, 20 surveys had to be excluded. This left a total of 120 surveys that were suitable for analysis, indicating a final effective response rate of 66.5%. The study participants were professionals in both the public and private sectors, with 55 in the former and 65 in the latter. They represented a diverse array of backgrounds, enhancing the richness of the data collected. The following section presents an in-depth analysis of the demographic characteristics of these study participants. All participants had worked in substance

use disorder (SUD) treatment settings for at least one year in Australia. Table 12 provides a comprehensive overview of the AOD practitioners who participated in the study.

Table 12 Demographic information of AOD Participants

Variable		**Frequency**	**Per cent**
Gender	Male	23	19.2
	Female	84	70
	Nonbinary/third gender	9	7.5
	I prefer not to say	4	3.3
Age	24 or under	14	11.7
	26-35 Years old	24	20
	36-49 Years old	39	32.5
	50-64 Years old	37	30.8
	65+ Years old	6	5
Education Level	Diploma /Advanced diploma /certificate (I-IV)	25	20.8
	Undergraduate degree	52	43.3
	Postgraduate degree/master	38	31.7
	Other	5	4.2
Sector of employment	Government	51	42.5
	Private (NGO)	69	57.5
Geographical location	Metropolitan	63	52.5
	Rural	37	31.8
	Remote	20	16.7
Behavioural Intention (The intention to use digital health in the future)	Strongly disagree	0	0
	Disagree	0	0
	Neutral	6	5
	Agree	28	23.5
	Strongly agree	86	71.5
Use Behavior of digital health (The kind and intensity of digital health platforms)	The phone call /Email	120	100
	Mobile app related to substance dependency	80	66
	Video conference (Skype, Zoom, WhatsApp&....)	78	65
	My organisation’s software	112	93
	Other (Big data, Cloud computing, health sensing)	3	2.5

6.2.1 Gender and Age

Among the participants in this study, females constitute the largest group, making up 70.0%. This is significantly higher than the 19.2% male representation. This is quite representative of the population as the social work field is female-dominated. A minority of 7.5% identify as nonbinary or third gender, and a small fraction of approximately 3.3% preferred not to disclose their gender.

Regarding age distribution, 11.7% of the participants are 24 years old or under, forming the youngest group in the study. The next age bracket, 26 to 35 years, comprises a slightly larger group, accounting for 20% of the participants. The 36 to 49 years bracket is the most represented age group, making up approximately 32.5% of the total. Close behind, those in the 50 to 64 age bracket account for nearly 30.8% of the participants. Lastly, the least represented group in this study is those aged 65 years and older, constituting about 5% of the total.

6.2.2 Level of Education and Sector of Employment

Among the participants, around 20.8% hold a “Diploma / Advanced Diploma / Certificate (I-IV),” forming a notable portion of the participant base. However, the group with an “Undergraduate degree” is the largest, comprising approximately 43.3%. Not far behind, participants with a “Postgraduate degree/master's” comprise a substantial segment, accounting for about 31.7% of the population. A small fraction, approximately 4.2%, fall under “Other” education levels. In terms of the employment sector, about 42.5% of the participants are associated with the government sector, again forming a significant part of the participant base. However, those employed in the private (NGO) sector constitute the majority, making up approximately 57.5% of the total participants.

6.2.3 Geographical Location

Over half of the participants, approximately 52.5%, are located in metropolitan areas, representing the largest group. A substantial number of participants, around 30.8%, are based in

rural areas. The smallest group consists of those located in remote areas, forming approximately 16.7% of the total participants.

6.2.4 Behavioural Intention and The User Behaviour of Digital Health

The study found that the participants had a high intention to use digital health tools in the future. Interestingly, none of the participants selected “Strongly disagree” or “Disagree”, indicating a general positive or neutral inclination towards the future use of digital health. A small fraction, approximately 5.0%, remained “Neutral”. A more significant segment of participants, around 23.3%, agreed with the statement, showing their intention to use digital health in the future. However, the most striking finding is that a significant majority, approximately 71.7%, strongly agree with the statement, indicating a high intention to use digital health in the future.

Not surprisingly, all participants, representing 100% of the total, reported using phone calls or emails as part of their digital health engagement. A considerable portion, approximately 66.7%, use a mobile app related to substance dependency. Close to this, around 65.0% of participants utilise video conference tools such as Skype, Zoom, and WhatsApp. Most notably, a significant majority, about 93.3% of participants, use their organisation’s software. However, a small fraction of participants, approximately 2.5%, reported using other digital health technologies, including big data, cloud computing, and health sensing.

6.3 Statistical Analysis

6.3.1 Structural Equation Modelling

Structural Equation Modelling (SEM) is a robust statistical technique extensively employed to analyse complex relationships between multiple variables. It is beneficial for investigating causal relationships and testing intricate theoretical models. SEM enables researchers to probe both direct and indirect relationships among various observed and latent variables and to estimate the strength and significance of these relationships. Due to its capability to model complex systems, SEM finds wide applications in various research fields, including psychology, sociology, and economics (Barrett, 2007; Streiner, 2006).

SEM is confirmatory, underscoring the necessity of specifying and testing the entire model based on the samples and variables used in the analysis. It requires careful consideration of numerous parameters, such as variance, covariance, and path coefficients. This understanding allows researchers to specify and test the entire model precisely based on the variables and samples involved in the calculations. Moreover, it is vital to identify all relationships used in the model before commencing the analysis (Thakkar & Thakkar, 2020).

There are distinct types of structural equation models, including linear regression models, factor analysis, confirmatory factor analysis (CFA), and path models. This study focuses explicitly on Structural Equation Modelling (SEM) as described by (SEM) (Jöreskog & Goldberger, 1975), which is the focus of this study. The software chosen for this study is AMOS, which stands for “analysis of a moment structures” and serves as an add-on module to SPSS. It is specialised for tasks like Structural Equation Modeling, path analysis, and confirmatory factor analysis. AMOS provides numerous advantages, including a user-friendly visual interface that enables researchers to create and modify models easily using intuitive drawing tools. Furthermore, AMOS excels at performing computations for Structural Equation Modeling (SEM) and effectively presenting the results of these analyses (Arbuckle, 2011; Kline, 1998).

One of the main disadvantages of Structural Equation Modeling (SEM) is its complexity, which requires a deep understanding of both the theoretical model and the statistical assumptions. SEM demands large sample sizes for stable estimates, making it less suitable for smaller studies. Additionally, its reliance on latent variables and multivariate normality can lead to challenges in real-world data, which often violate these assumptions, causing inflated Type I errors. Researchers can also be tempted to overfit models by using statistical modifications without theoretical justification, leading to results that may not generalize well across different populations (Nachtigall, Kroehne, Funke, & Steyer, 2003; Preacher & Yaremych, 2023). The following section provides a comprehensive account of the procedures used for data preparation and analysis in this study.

6.3.2. Data Preparation and Normality

Before beginning the data analysis, a pre-data analysis and preparation phase were carried out on the raw data. The data preparation process involves cleaning and transforming the raw data into a suitable format for analysis. This may involve various steps, such as removing duplicates, correcting errors, handling missing data, and ensuring data is consistently formatted. Data preparation ensures the data is accurate, complete, and ready for further analysis (Kwak & Kim, 2017). By conducting thorough data preparation, researchers can have confidence in the reliability and validity of their analysis results.

Data screening is a crucial step in data analysis. It involves carefully examining the data to identify potential problems like errors, outliers, and missing data. By doing so, researchers can ensure data accuracy, address outliers appropriately, handle missing data, and manage response set issues that could impact the validity of the analysis. This research follows the data preparation and screening steps, and usable responses were entered into the SPSS 29 statistical package. A manual sample examination, where every fifth questionnaire was systematically selected and checked manually by comparation the entered data with the original

data, was conducted to help identify and rectify any potential errors in the data entry procedure, ensuring the reliability and integrity of the dataset for further analysis.

6.3.3 Missing Data Management

The absence of recorded data for a variable in the observation of interest is referred to as missing data or missing values. It is a common challenge in social research data analysis that can hinder accurate and comprehensive analyses, ultimately restricting the conclusions that can be drawn from the data (Graham, 2009). Properly addressing missing data is crucial to overcome these obstacles and ensure the validity of the results (Pampaka, Hutcheson, & Williams, 2016).

The most effective approach to managing missing data is proactively preventing the issue by carefully planning the study and ensuring accurate data collection (Scharfstein, Hogan, & Herman, 2012). This research employed various strategies to avoid missing data, including systematic study design, detailed documentation, pre-testing, setting targets for acceptable levels of missing data, real-time data monitoring, engaging at-risk participants, and recording reasons for withdrawals. Questionnaires with missing answers were eliminated from the study to maintain the data integrity. This decision was taken to avoid difficulties computing suitable measures like the Goodness-of-Fit-Index (GFI) in Structural Equation Modeling through AMOS (Gallagher, Ting, & Palmer, 2008)

Over six months, as stated in Section 6.2, 120 responses were sourced, representing a 60% response rate of the 200 questionnaires administered. According to Sekaran (2003), a survey response rate of 30% is generally considered acceptable, and the achieved response rate of 70.0% in this study is considered sufficient (Sekaran & Bougie, 2003).

6.3.4 Outliers Screening

In a research study setting, it is crucial to perform outlier detection on the data as they can significantly impact the findings of the data analysis. Outlier testing is identifying and analysing observations in a dataset with values substantially different from the importance of other

responses in the same dataset (D. Moore & McCabe, 2006). Outliers can be divided into two categories: univariate outliers, which involve unusual values on a single variable, and multivariate outliers, which involve an unusual combination of values across several variables (R. B. Kline, 2005).

This research examined univariate and multivariate outliers applying the residual Analysis (Tabachnick & Fidell, 2007), and the following steps were employed transparently. First, each variable was represented by its mean composite in the study, and these composites were standardised to identify univariate outliers. After that, cases with standardised values greater than the absolute value of 3.29 were identified as outliers (Tabachnick & Fidell, 2007). Thus, the outcome of this analysis indicated that there were no individual outlier instances with residuals higher than 3.29.

Furthermore, to identify multivariate outliers in this research, Cook's Distance value was utilised to examine the impact of outliers on the research data, as Hair et al. (2006) recommended. Cook's Distance was used to identify outliers in the x- and y-spaces. Cases whose Cook's D values exceeded 0.0069 (i.e., the Cook's D mean + two SDs, as per Norusis, 1991) were regarded as outliers (C. Kim & Storer, 1996). Hence, the analysis did not reveal any multivariate outliers, indicating that the data followed a normal distribution.

6.4 Results

6.4.1 Construct reliability and validity

Reliability and validity represent the fundamental attributes in assessing the worth of any measuring tool or instrument for sound research. Validity refers to the accuracy of what is being measured by an instrument and how effectively it measures it. Meanwhile, reliability refers to the level of confidence one can have in the data gathered from the instrument's use, which means to what extent the measuring tool eliminates random errors (Mohajan, 2017).

Evaluating the factor loading of scale items is essential to factor analysis. It measures the degree of association between each variable and factor. High-factor loading implies a strong association with a particular factor, while low-factor loading implies a weaker association. Factor loading helps researchers understand the extent to which each variable contributes to the identified factors.

Factor loadings below 0.4 are commonly considered low, and items with low loadings should be withdrawn or suppressed in factor analysis. This is because low-loading items do not contribute much to the overall factor structure and may add inaccuracy to the Analysis (Andy, 2005; De Vaus & de Vaus, 2013). To ensure the practical significance of all variables analysed in this study, a recommended factor loading cut-off of 0.50 was employed (Hair et al., 2006). This means only variables with a strong relationship with a particular factor were included in the analysis, while those with weaker relationships were excluded. As appeared in Table 13, the loading values of all items go beyond the cut-off level of 0.50.

Table 13 Factor Loading

1	Performance expectancy (PE)	PE-1	0.8
		PE-2	0.81
		PE-3	0.82
		PE-4	0.77
2	Social influence (SI)	SI-1	0.92
		SI-2	0.88
		SI-3	0.83
		SI-4	0.87
3	Effort expectancy (EE)	EE-2	0.9
		EE-3	0.8
		EE-4	0.86
4	Facilitating conditions (FC)	FC-2	0.7
		FC-3	0.84
		FC-4	0.79
5	Fear of COVID-19(FC19)-	FC-2	0.66
		FC-3	0.89
		FC-4	0.66
6	Clinicians' Self-Efficacy (SE)	SE-2	0.86
		SE-3	0.82
		SE-5	0.86
7	Trust in Digital Health (TR)	TR-1	0.52
		TR-2	0.73
		TR-3	0.89
		TR-4	0.86
		TR-6	0.76
8	Client Digital -Literacy	DL-1	0.72
		DL-2	0.83
		DL-4	0.66
9	Privacy Concern (PC)	PC-1	0.83
		PC-2	0.89
		PC-3	0.69
10	Possibility of Establishing a Therapeutical Alliance	TA-1	0.58
		TA -2	0.85
		TA-3	0.69
		TA- 4	0.89

- Reliability

Nevertheless, in technology acceptance models, reliability refers to the extent to which the indicators or variables used are consistent and stable in measuring what they are intended to measure. This means that the focus is on the stability and consistency of the measurement itself rather than the presence of random errors (Singleton Jr, Straits, Straits, & McAllister, 1988). Venkatesh (2003) evaluated the reliability of the UTAUT instrument multiple times throughout its development and found that all of the reliability coefficients were around 0.70.

In this study, the reliability analysis of all constructs of the UTAUT model was carried out using SPSS Version 22, the most used measure of reliability in SPSS, and a Cronbach's alpha value in the range of 0.7 is considered acceptable and indicates adequate internal consistency. The measures' reliability for all constructs is deemed adequate, as indicated by Table 5-5. The formulas for Coefficient Alpha and Omega are shown in Equation 1 and Equation 2, respectively.

Equation 1: α (Cronbach's Coefficient Alpha)

$$\alpha = \frac{k}{k-1}\left[1 - \frac{\sum_{i=1}^{k} \sigma_{ii}}{\sum_{i=1}^{k} \sigma_{ii} + 2\sum_{i<j} \sigma_{ij}}\right]$$

- ***k*** is the number of items in a construct,
- ***σii*** is the item ***i*** observed variances, and,
- ***σij*** is the observed covariance of items ***i*** and ***j***.

$$\omega = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k} \psi_i}$$

Where:

- **λi** is the factor loading of item i,
- **ψ** is the uniqueness of item I,
- **k** is the number of items in the factor

Table 14 presents the results of the reliability analysis, which show that all the constructs had a high reliability of over 0.7, suggesting solid internal consistency. Furthermore, some items were deleted to strengthen the alpha value after the reliability test. Thus, in the final questionnaire for the study, each construct has at least three scale items.

Table 14 Reliability and Variance Extracted for Construct.

	CONSTRUCT	CA	CR	AVE
1	Performance Expectancy	.806	0.877	0.640
2	Effort Expectancy	.865	0.891	0.733
3	Facilitating Conditions	.790	0.858	0.671
4	Social Influence	.947	0.945	0.812
5	Trust in Digital Health	.949	0.749	0.546
6	Privacy Concern	.821	0.848	0.652
7	Clinicians' Self-Efficacy	.844	0.950	0.864
8	Fear of COVID-19	.777	0.823	0.616
9	Client Digital -Literacy	.821	0.848	0.652
10	Possibility of Establishing a Therapeutical Alliance	.585	0.824	0.544

- Validity

Construct validity verifies the accuracy of constructs by examining their associations with other variables that are either indicators of or are theoretically linked to the construct under investigation (Locke, 2012). Turocy (2002) suggests that factor analysis is commonly connected to construct validity and is considered one of the analytical techniques for evaluating construct validity (Turocy, 2002).

The assessment of validity was undertaken through both convergent and discriminant validity tests. Convergent validity probes the degree of correlation between measurements of the identical construct. On the other hand, discriminant validity defines how distinct one measure is from other measures, as described by Kline (2005) (T. J. Kline, 2005). The criteria set by Fornell and Larcker (1981) are used to gauge both construct and discriminant validity (Fornell & Larcker, 1981). The average variance extracted (AVE) determines construct validity (see Equation 3).

Validity is confirmed when the AVE surpasses 0.5. Discriminant validity is recognised when the square root of the AVE for a given construct is less than its maximum shared variance (MSV).

Equation 3 - Average Variance Extracted (AVE)

$$AVE = \frac{\sum_{i=1}^{p} \lambda_i^2}{\sum_{i=1}^{p} \lambda_i^2 + \sum_{i=1}^{p} Var(\varepsilon_1)}$$

- ***p*** is the number of items,
- ***λi*** is the factor loading of item ***i***, and,
- ***Var(εi)*** is the variance of the error of item ***i***

Table 15 presents the discriminant validity results for the various constructs covered in the study. Discriminant validity reveals that each construct is distinct and measures different underlying concepts. The values in the table are the square root of the Average Variance Extracted (AVE) for each construct, indicating how much variance the construct's indicators capture.

Table 15 Result Presentation for Validity.

N	CONSTRUCT	FAC_C	PE_E	SOCIAL	EFFORT	FC19	SELF	TRUST	BEHAV	DGTL	PRIVACY
1	Facilitating Conditions	**0.819**									
2	Performance Expectancy	0.088	**0.800**								
3	Social Influence	0.106	0.100	**0.901**							
4	Effort Expectancy	0.435	0.209	0.287	**0.856**						
5	Fear of Covid-19	0.200	0.128	0.388	0.114	**0.785**					
6	Clinicians' Self-Efficacy	0.335	0.073	0.184	0.150	0.546	**0.930**				
7	Trust in Digital Health	0.868	0.125	0.131	0.298	0.573	0.462	**0.739**			
8	Possibility of Establishing a Therapeutical Alliance	0.362	0.460	0.199	0.304	0.464	0.330	0.674	**0.738**		
9	Client Digital - Literacy	0.434	0.388	0.169	0.244	0.440	0.478	0.669	0.522	**0.740**	
10	Privacy Concern	0.035	0.116	0.030	0.073	346.000	0.408	0.604	0.526	0.568	**0.807**

6.4.2 Goodness of Fit (GOF)

After evaluating reliability and validity, the researchers utilised goodness-of-fit indices to gauge how well a given sample data fit the data. Goodness-of-fit indices are statistical tools used to assess the level of conformity between an observed data set and a hypothesised model (Anderson & Darling, 1954). This enabled the researchers to determine whether the models were valid for their collected data.

A variety of fit tests are available to researchers. The chi-square $\chi 2$ statistic serves as a fundamental and crucial measure for evaluating a model's absolute fit. A model is generally considered to have a good fit if the p-value associated with the $\chi 2$ statistic is greater than the conventional significance level (often 0.05), indicating a lack of a significant difference between observed and expected data (Hartmann, Guthöhrlein, Siebert, Luehr, & Söding, 2013; D. Lewis & Burke, 1949). Nevertheless, according to the literature, the chi-square statistic is highly susceptible to both a large sample size and a complex model (Kyriazos, 2018). The dataset

obtained in this study consists of a sample size exceeding 100 cases and meets the suggested threshold for ensuring the stability of structural equation modelling (SEM) Analysis (Hair et al., 2006). In this research, although the model showed multivariate normality and the sample size was adequate, additional tests of fit were conducted alongside the Chi-square statistic to ensure agreement on the suitability of the model. Table 16 presents the main fit statistics applied and their acceptable levels.

In order to comprehensively assess the fitness of the model, both absolute and incremental fit indices were employed in conjunction with the Chi-square test. Absolute fit indices are utilised to evaluate the degree to which the model adequately captures the observed data from the sample, thus serving as a means to assess the overall fitness of the model (Eid, Nussbeck, Geiser, Cole, Gollwitzer, & Lischetzke, 2008). The normed Chi-square statistic, determined by dividing the Chi-(Hubbard & Lindsay, 2008)e value by the degrees of freedom, is an absolute fit index that is frequently used to assess model fit. Generally, a value below 2, accompanied by a p-value greater than 0.5, is considered an acceptable fit (Hair et al., 2006). The Goodness-of-fit Index (GFI) is often used as an absolute fit index in research studies, as it measures how closely the covariances of the latent variables predicted by the model match the observed data (T. D. Smith & McMillan, 2001). The Adjusted Goodness-of-fit Index (AGFI) is a modified version of the GFI that considers both the degrees of freedom and the number of variables in the model (Mulaik, James, Van Alstine, Bennett, Lind, & Stilwell, 1989). Although the GFI and AGFI are widely used in research, some critics contend that these indices are unreliable and excessively influenced by sample size and should not be employed (Meade, Johnson, & Braddy, 2008).

In contrast, the Root-Mean-Square Error of Approximation (RMSEA) is regarded as less susceptible to sample size and distribution effects in comparison. Meanwhile, the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are considered incremental fit indices, indicating the degree of improvement in model fit in relation to a baseline null model with uncorrelated observed variables (F. F. Chen, 2007). Table 16 presents how well the various models fit the

data. In the initial comparisons, the Default model has a chi-square value of 861.782 with 250 degrees of freedom. Generally, a value closer to 1 indicates a superior fit, but it is crucial to note that a larger sample size can make this measure more sensitive. The table also displays a variety of results: NFI (.843) and RFI (.816) are on the lower side, whereas IFI (.918), TLI (.903), and CFI (.917) suggest a more satisfactory fit.

On the other hand, the Saturated model perfectly aligns with the data, as anticipated, while the Independence model, which presumes no interconnections, performs poorly with values of 0. The RMSEA score of 0.061 for the Default model falls within the acceptable bounds, suggesting a decent fit with the data. Overall, the Default model appears to fit the data reasonably well.

Table 16 Goodness of Fit

Baseline Comparisons

Chi-square = 861.782

Degrees of freedom = 250

Probability level = .000

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI	RMSEA
Default model	.843	.816	.918	.903	.917	.061
Saturated model	1.000		1.000		1.000	.194
Independence model	.000	.000	.000	.000	.000	

6.4.3 Normality

Numerous statistical methods and multivariate techniques depend on the normal distribution and the assumption of normality to draw meaningful inferences. This is due to normality's crucial role in ensuring the accuracy and validity of many statistical analyses (Johnson & Wichern, 2007).

Various methods for assessing normality are available. In the univariate setting, graphical methods such as Q-Q plots, histograms, and box plots can be used (Ghasemi & Zahediasl, 2012), along with statistical tests like the Kolmogorov-Smirnov test and Shapiro-Wilk and Anderson-Darling test. It is important to consider the marginal distribution and linear combinations for multivariate data, and tests like Royston's and Mardia's tests can be applied. In cases where the normality assumption cannot be met, non-parametric methods or transformations can serve as suitable alternatives (Johnson & Wichern, 2007).

Field (2005) emphasises that the sample size can impact the choice of statistical methods used for testing normality. Consequently, it is recommended to assess univariate normality by considering both skewness and kurtosis values and visually inspecting the data's histogram. This comprehensive approach ensures a more accurate determination of normality and aids in selecting appropriate statistical techniques for subsequent analyses (Field, 2005). Therefore, a bell-shaped distribution in the data suggests normality, and skewness and kurtosis values close to zero are considered ideal indicators of normality. Generally, a skewness index with an absolute value no greater than 3.0 and a kurtosis index with an absolute value no greater than 10.0 are deemed acceptable for normality assessment (Kline, 2015).

In this study, the primary method used to test univariate normality was inspecting the data histogram for each construct. The histogram examination reveals that the shape of each univariate distribution was normal and deemed acceptable. Furthermore, the results presented in

Table 17 indicate that the values of all variables fell within the acceptable range of skewness and kurtosis, further confirming the normality of the data.

Table 17 Assessment of Normality.

Variable	min	max	skew	c.r.	Kurtosis	c.r.
TR1	1	5	-0.453	-2.924	-0.406	-1.312
PC_1	1	5	-1.217	-7.856	0.353	1.141
PC_2	1	5	-1.142	-7.371	0.175	0.564
PC_3	1	5	-0.858	-5.537	-0.542	-1.749
DL_1	1	5	-1.507	-9.727	2.211	7.137
DL_2	1	5	-0.973	-6.284	0.221	0.714
DL_4	1	5	-1.425	-9.197	1.768	5.706
TA1	1	5	-0.345	-2.229	-0.561	-1.811
TA2	1	5	-0.245	-1.583	-0.793	-2.558
TA3	1	5	-0.374	-2.412	-0.694	-2.241
TA 4	1	5	-0.403	-2.6	-0.642	-2.07
TR2	1	5	-0.582	-3.755	-0.217	-0.699
TR3	1	5	-1.01	-6.516	0.103	0.332
SE_2	1	5	-0.12	-0.777	-0.456	-1.473
SE_3	1	5	-0.244	-1.575	-0.366	-1.183
SE_5	1	5	-0.804	-5.188	0.462	1.49
FC_2	1	5	-0.511	-3.301	-0.642	-2.071
FC_3	1	5	-0.594	-3.833	-0.535	-1.727
FC_4	1	5	-0.625	-4.032	-0.207	-0.669
FC2	1	5	-0.271	-1.751	-0.687	-2.219
FC3	1	5	-0.386	-2.49	-0.555	-1.791
FC4	1	5	-0.523	-3.377	-0.164	-0.53
EE2	1	5	-0.737	-4.758	-0.352	-1.136
EE3	1	5	-0.66	-4.263	-0.542	-1.751
EE4	1	5	-0.693	-4.475	-0.294	-0.95
SI1	1	5	-1.094	-7.059	0.113	0.365
SI2	1	5	-0.854	-5.515	-0.367	-1.185
SI3	1	5	-0.955	-6.165	-0.1	-0.322
SI4	1	5	-1.079	-6.963	0.124	0.399
PE1	1	5	-0.123	-0.792	-0.908	-2.932
PE2	1	5	-0.252	-1.627	-1.001	-3.229
PE3	1	5	-0.274	-1.766	-0.662	-2.137
PE4	1	5	-0.351	-2.263	-0.52	-1.677
Multivariate					76.589	12.598

6.4.4 Sample Adequacy

To determine the suitability of the dataset for factor analysis the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity are commonly used to determine the suitability of a dataset for factor analysis employed. The KMO measure evaluates the overall sampling adequacy of the data, while Bartlett's test assesses the degree of correlation between the variables in the dataset. A significant result (p-value less than 0.05) indicates that the dataset is suitable for factor analysis (Bucerius et al., 2003; De Vaus & de Vaus, 2013). In this research, KMO value was 0.91, and Bartlett's test calculations were $\chi 2 = 2217.620$, df = 140, and Sig = 0.000. The results established sample adequacy.

6.4.5 Hypothesis tests

The results of the hypothesis testing are presented in Table 18 and illustrated in Figure 24. This study operated on the assumption that many factors can affect the use and acceptance of digital health by AOD Practitioners. As per the data in Table 18 of the 10 hypotheses proved to be statistically significant and held substantive meaning, with values ranging from -0.104 to 0.437. Notably, the constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions were found to positively influence the behavioural intention (BI) construct (0.437, $p < 0.001$), thus affirming H1, H2, H3, and H4.

The findings also indicate that the Trust in Technology (TR) construct in digital health technology positively influenced the 'BI_AOD' construct (**0.292, $p < 0.001$**), thus affirming **H5**. However, 'Privacy Concern' negatively influences 'BI_AOD', with a weight of -0.292, which means that as privacy concerns increase, 'BI_AOD' tends to decrease. This relationship is statistically significant as well, Supporting **H6**. 'FC19' negatively influences 'BI_AOD' with a weight of -0.104. However, the p-value of 0.195 suggests that this relationship is not statistically significant, meaning the study cannot confidently say that 'FC19' influences 'BI_AOD'; as a result, **H7** was not substantiated.

Additionally, the Clinician's Self-Efficacy (SE) construct positively influenced 'BI_AOD' with a substantial value of **0.113, p < 0.001**, lending support to **H8**. **Lastly**, the construct representing the Possibility of Establishing a Therapeutic Alliance/Virtual Intimacy (VI) can predict the 'BI_AOD' of, given its value of **0.316, p < 0.001**; hence, **H9** was supported and statistically significant. In summary, most of the factors listed significantly influence 'BI_AOD,' either positively or negatively, except for 'FC19'.

Table 18 Hypothesis Testing.

Hypothesis	Independent Variables	Dependent Variable	Standardised Regression Coefficients	P(>|z|)	Outcome
H1	Performance Expectancy	Technology use and acceptance	0.437	***	Supported
H2	Effort Expectancy	Technology use and acceptance	0.232	***	Supported
H3	Social Influence	Technology use and acceptance	0.122	***	Supported
H4	Facilitating Conditions	Technology use and acceptance	0.251	***	Supported
H5	Trust in Digital Health	Technology use and acceptance	0.292	***	Supported
H6	Privacy Concern	Technology use and acceptance	-0.292	***	Supported
H7	Fear of COVID-19(FC19)	Technology use and acceptance	-0.104	0.195	Not Supported
H8	Clinician's Self-Efficacy	Technology use and acceptance	0.113	***	Supported
H9	Client digital-Literacy	Technology use and acceptance	0.316	***	Supported
H1O	Possibility of Establishing a Therapeutical Alliance	Technology use and acceptance	0.412	***	Supported

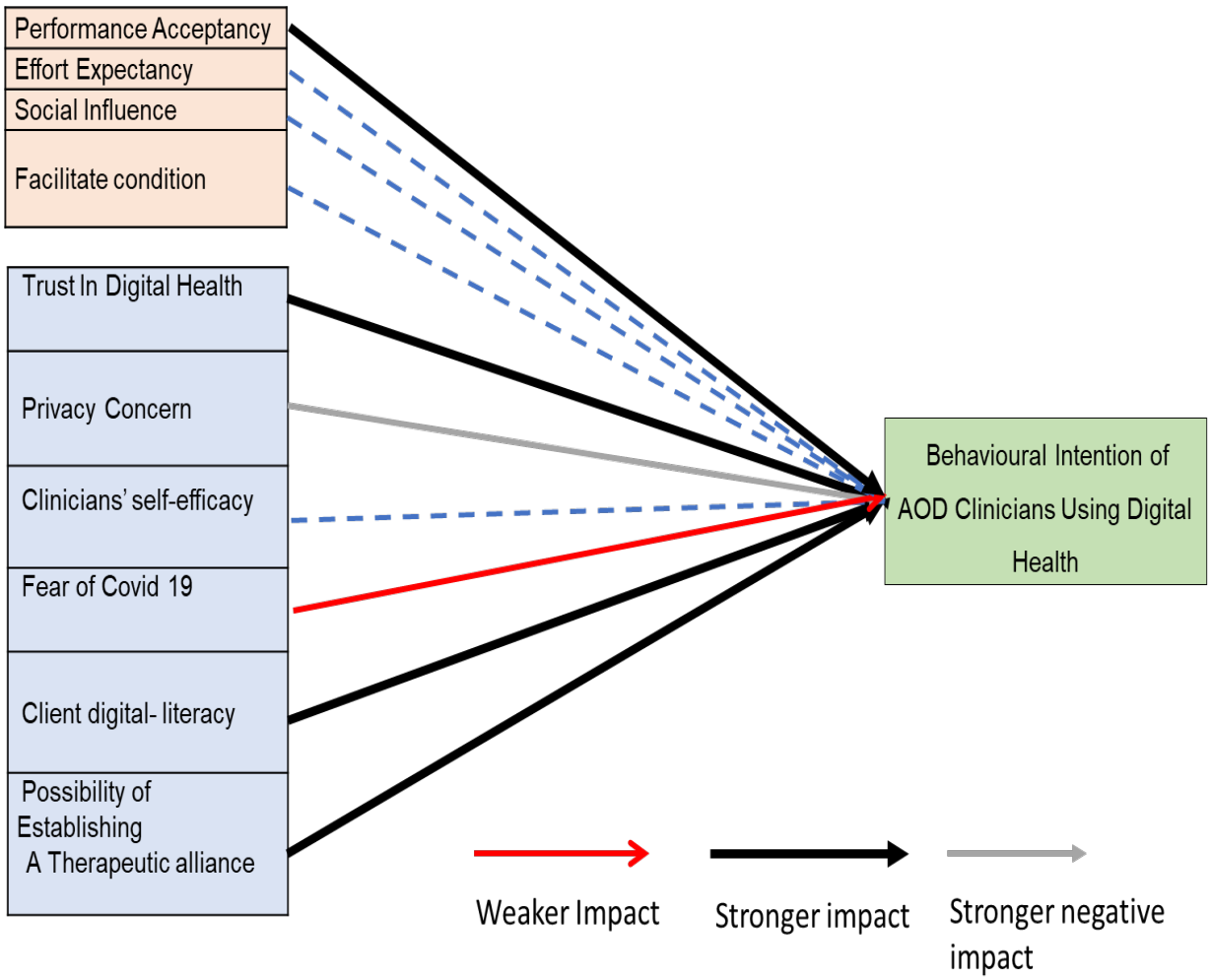

Figure 24 Hypothesis Testing

6.5 Discussion

The analysis presented robust statistical evidence that clinicians' behavioural intention (BI) and their use of digital health technology were positively influenced by factors such as performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), trust (TR), Concern About Privacy (PC), and Clinician's Self-Efficacy (SE). The path analysis supported all but one of the hypotheses. The primary aim of this study is to contribute to the existing body of knowledge and seek to provide a deeper understanding of the factors that influence the adoption of digital health technologies among AOD workers. In this section, this study validates these key constructs and provides empirical evidence for their significance in the digital health context.

H1: There is a direct and positive relationship between performance expectancy and behavioural intention of AOD workers using digital health.

According to Venkatesh et al. (2003), Performance Expectancy (PE) is an individual's belief in how a particular system will enhance their job performance. Essentially, the perceived advantages of incorporating a system into service delivery can positively influence the adoption rate of that service (Tojib & Tsarenko, 2012) and contribute to satisfying healthcare experiences for users(Slade, Williams, & Dwivedi, 2013).

These research findings support Hypothesis H1, which suggests a positive relationship between the level of performance expectancy and the Behavioral intention of AOD workers to adopt digital health. This result is in line with previous studies that have used UTAUT to investigate user adoption (Alam, Hu, Hoque, & Kaium, 2020; Gagnon, Ngangue, Payne-Gagnon, & Desmartis, 2016; Gu et al., 2021; Khan, Yu, Hameed, Khan, & Waheed, 2018).

Furthermore, the importance of PE in influencing the behavioural intention and adoption of digital health can be attributed to the numerous benefits that digital health offers to both clients and clinicians, including convenient access to valuable information and seamless online therapy

sessions, regardless of time or location. This has been especially advantageous during the COVID-19 pandemic, where in-person interactions have been limited. The study's findings suggest that clinicians should recognise and acknowledge the benefits associated with digital health to develop a positive behavioural intention towards its adoption.

H2: There is a direct and positive relationship between effort expectancy and behavioural intention of AOD workers using digital health.

This study defines the effort expectancy variable as the level of ease associated with using digital health. It was assessed by the perceived ease of learning, using, and becoming skilled at using these systems.

The research findings support the hypothesis that a meaningful relationship exists between effort expectancy and the behavioural intention to use digital health. This outcome is consistent with earlier research conducted using the UTAUT framework in this field (Boontarig, Chutimaskul, Chongsuphajaisiddhi, & Papasratorn, 2012; Lian, 2015).

The study's results suggest that individuals are more likely to have a positive attitude towards e-health technology when they perceive it as simple and user-friendly.

H3 There is a direct and positive relationship between social influence and BI of AOD workers using digital health.

In this study, the term' social influence' refers to an individual's perception of the significance of others' opinions regarding their use of digital health services. The study's results suggest that social influence significantly shapes clinicians' intentions to adopt digital health services in the Australian SUD industry.

This finding is in line with other research that suggests that social influence plays a crucial role in technology acceptance and adoption and has employed UTAUT to investigate this

phenomenon (Ahmad & Khalid, 2017; Alhiary, 2023; Bhatt, Singh, & Aslam, 2023; Sun, Wang, Guo, & Peng, 2013).

The role of social influence in promoting technology adoption can be vital for clinicians who may be new to digital health interventions. In this context, users may rely on the recommendations and experiences of others when making adoption decisions. Therefore, within a SUD treatment intervention, promoting interactions between clinicians and exposing them to each other's activities may encourage a higher adoption rate of desired behaviours. For example, this could involve creating opportunities for peer-to-peer learning, sharing success stories, and facilitating discussion groups to foster community and promote exchanging ideas and best practices. By doing so, clinicians may be more likely to adopt digital health interventions and engage in the desired behaviours, ultimately improving the client's treatment outcomes.

H4- There is a direct and positive relationship between facilitating conditions and BI of AOD workers using digital health.

Facilitating conditions refer to the accessibility of resources that enable digital health tools. These include participants' perception of their ability to access the necessary resources, knowledge, and technical support. Previous studies integrated into the UTAUT model have indicated that facilitating conditions, such as users' technical proficiency, system infrastructure, and technical maintenance, significantly impact their satisfaction with digital health (W.-I. Lee, Fu, Mendoza, & Liu, 2021).

The study's results align with earlier research and suggest that facilitating conditions significantly impact users' behavioural intentions to adopt digital health tools (M. M. D. Alam, Alam, Rahman, & Taghizadeh, 2021; Wrzosek, Zimmermann, & Balwicki, 2020). Therefore, the hypothesis of the results supported H4.

H5 There is a direct and positive relationship between trust and BI of AOD workers using digital health.

In this study, trust refers to the belief that a particular technology will function adequately and consistently over time. It has been identified as the most crucial factor influencing a user's digital health behaviour (Kowitlawakul, Chan, Pulcini, & Wang, 2015). As trust increases, clinicians may perceive less risk, leading to a greater intention to accept digital health. This highlights the critical role of trust in adopting and accepting digital health technologies.

According to the survey results, most clinicians (e.g. 75%) reported having an elevated level of trust in digital health, while a smaller percentage (e.g. 10%) expressed distrust towards it. Additionally, a considerable proportion (e.g. 80%) agreed they rely on digital health tools to assist them in their work.

The study findings indicate a significant relationship between clinicians' trust in digital health and its impact on their utilisation of e-tools. This is similar to another research (Ek, Eriksson-Backa, & Niemelä, 2013; Gu et al., 2021). Thus, clinicians' trust in digital health plays a significant role in their decision-making process regarding digital health tools and thus hypothesis H5 was supported.

H6 There is a direct and negative relationship between Clinicians' concerns about privacy and BI of AOD workers using digital health.

Clinicians' concerns about privacy significantly affected AOD workers' behavioural intention to use digital health. Clients' health and personal information represent a repository of sensitive data, particularly in the SUD field. In the study context, clinicians' concern about privacy refers to the extent to which private files and information are stored and transmitted so that unauthorised third parties or entities are prevented from accessing them. These

concerns were evident in some of the clinicians who participated in our qualitative interviews. This can have a negative impact on the acceptance of digital health among AOD workers.

This finding aligns with a study by (Dhagarra, Goswami, & Kumar, 2020; Li, Gupta, Zhang, & Sarathy, 2014; Sankaranarayanan & Sallach, 2014) on Internet banking adoption that found privacy affects individuals' intention to use digital health technology. To the best of our knowledge, this study is the first attempt to investigate the role of privacy in the acceptance of digital health tools among AOD clinicians utilising the UTAUT model.

H7- There is a direct and positive relationship between the fear of COVID-19 and the BI of AOD workers using digital health.

The COVID-19 pandemic has influenced the adoption and utilisation of digital health and technology (Bokolo, 2021; Keesara, Jonas, & Schulman, 2020). While the qualitative research data indicated one set of findings, our quantitative analysis told a different story about the Fear of COVID-19.

Undoubtedly, the initial stages of the pandemic marked the peak of anxiety, emotional distress, dread of isolation, and uncertainty about managing the crisis effectively, which were some of the primary contributors to the high fear felt by AOD clinicians in early 2022. However, With the introduction of the COVID-19 vaccine and booster shots, the fear of COVID-19 changed as adaptive reactions driven by fear have played a crucial role in human survival (Six, de Vadder, Glavina, Verhoest, & Pepermans, 2023). Analysing results within the evolving context of the crisis over time can explain the variance in results across different stages of the research.

H8- There is a direct and positive relationship between the clinician's self-efficacy and the BI of AOD workers using digital health.

According to Bandura (1986), self-efficacy is defined as an individual's belief in their ability to perform a particular task successfully, not solely based on their skills, but also on their ability to utilise those skills effectively (Bandura, 1986). Therefore, in the context of this study, self-efficacy refers to a clinician's belief that they have the necessary skills and abilities to utilise digital health technology for SUD treatment successfully.

Individual differences are considered crucial in the domain of technology acceptance. By acknowledging variances among clinicians, treatment providers can develop individual user profiles that can assist in technology acceptance through personalised interventions to enhance users' beliefs about specific technologies. The finding of this study highlights that a minority of clinicians (20 %) could use any new digital health tool if no one were around them to tell them what to do. However (37%) needed more time or support.

This research revealed that clinicians' self-efficacy significantly shapes their intentions to adopt digital health services. This finding is in line with other research that suggests clinicians who possess a strong sense of self-efficacy are more likely to benefit from digital health platforms and feel confident in their ability to learn and adapt to digital health (Alharbi & Drew, 2019; Rahman, Ko, Warren, & Carpenter, 2016; Tao, Shao, Wang, Yan, & Qu, 2020; Zhang et al., 2017).

H 9- There is a direct and positive relationship between Client E-Literacy and Access and the BI of AOD workers using digital health.

The term digital health literacy refers to people's capacity to search for, locate, comprehend, and evaluate health information obtained from electronic sources (Norman & Skinner, 2006a). Clients also need to have access to reliable Internet and smartphones to be able to receive the needed health care services. This can impact the accessibility and utilisation of digital health (J. Lee & Rho, 2013). As highlighted in other research, the correlation between e-health literacy,

utilisation, and acceptance of digital health should not be disregarded (Alsahafi, Gay, & Khwaji, 2022; Walsh et al., 2017).

In this study, clinicians reported (50%) that their clients cannot afford a smartphone. Moreover,50% strongly agreed or agreed that clients do not have the money to get an Internet connection. This observation is consistent with other studies, emphasising that digital health could pose challenges for specific at-risk populations. These include the elderly, individuals with health conditions, those without stable housing, and those without access to information technology services (Kaihlanen et al., 2022; B. Smith & Magnani, 2019).

H10- There is a direct and positive relationship between the possibility of establishing a therapeutic alliance /virtual intimacy and the BI of AOD workers using digital health.

Extensive research has established that the relationship quality between clients and clinicians is the primary determinant of client progress, regardless of the therapeutic techniques or theoretical approaches (Norcross & Lambert, 2018; Poston & Hanson, 2010). Digital health platforms can effectively establish and maintain a therapeutic alliance (Richards et al., 2018), enhancing clinicians' acceptance and adoption of these platforms in healthcare settings.

This study defined the therapeutic alliance as the level of partnership and collaborative effort between a therapist and a client. The participants who reported a positive and stronger therapeutic alliance in digital health settings were significantly associated with positive treatment outcomes and higher levels of technology acceptance. Most participants (N=80) reported that their online therapy sessions were as supportive as their face-to-face sessions. However, they were neutral (N=90) about their confidence in their abilities during online therapy sessions. However, most participants (N=75) agreed they could establish a collaborative approach when working with clients during online therapy sessions. Thus, H10 was supported.

6.6 Summary

This section delves into the outcomes of the comprehensive online survey conducted during the quantitative part of the research study. The chapter explains the data preparation and purification of measures undertaken to ensure the accuracy of the results. The validity and reliability of the data were assessed, and the congruity of the congeneric and structural models was evaluated. Furthermore, the chapter explores the finding of hypothesis testing, revealing intriguing findings regarding some variables.

Based on the research findings, the UTAUT model is a suitable framework for analysing the study's subject. Furthermore, the model has been effectively adapted by incorporating additional variables. Almost all of these variables have significantly impacted the behavioural intention of AOD clinicians using digital health in SUD treatment settings.

7.0. CHAPTER SEVEN-CONCLUSION

7.1. Overview

Over the past decade, the swift global adoption of digital strategies has fundamentally reshaped healthcare. This shift has marked the onset of the "e-Health" era, emphasising the application of virtual technologies in health, a subset of the all-encompassing "digital health" domain. As digital strategies become increasingly pivotal in bolstering health systems to realise Sustainable Development Goals and ensure universal health coverage, several challenges, such as ethical issues, privacy, and cost, have emerged. This study examines incorporating digital health tools in treating substance use disorders. It aims to provide a nuanced understanding of the attitudes and acceptance behaviours of AOD clinicians in Australia towards innovative e-tools. By determining the catalysts and barriers to adoption, the study can strategies more effectively to optimise the integration of these services.

The study made a significant theoretical contribution by developing a model for digital health use by AOD clinicians for SUD treatment. The model was developed by integrating the technology adoption, specifically UTAUT and digital health literatures and then validating it with a mixed method approach and SEM analysis. The study embarked on an initial qualitative phase to empirically validate the conceptual model, refining the overarching framework and gauging its credibility. Subsequently, a quantitative approach was adopted—leveraging an online survey to collate insights from a random cohort of clinicians engaged in SUD treatment. The hypotheses derived from the conceptual models were tested, and the constructs within the models were validated through data analysis. This involved utilising various statistical techniques to examine the variables and assess the models' overall fit. The results of the analyses support the validity of the conceptual models and the hypotheses derived from them.

This chapter will address the research questions by explaining both the theoretical and methodological contributions of the study, along with its practical implications. It clarifies the

prevailing practices and trends in the integration of digital health technologies by clinicians managing Substance Use Disorders (SUDs) in Australia and identifies the theoretical frameworks that best explain the factors influencing clinicians' acceptance and use of these technologies. Additionally, the chapter explores the perceived benefits and challenges associated with digital health technologies from the clinicians' perspectives and presents evidence-based strategies to enhance their acceptance and effective implementation. It also discusses how these strategies can be adapted for broader adoption in related fields, such as social work and public health. Furthermore, the chapter addresses the study's limitations, considering sample size, data collection methodologies, and possible confounding factors, lessened learned and potential avenues for future research.

7.2. Research Contribution

The present research has provided both theoretical and methodological contributions, as well as insights into practical implications.

7.2.1. Theoretical Contribution

This research makes a significant theoretical contribution by developing a model for the adoption and effective design and utilisation of digital health technologies in SUD treatment environments. This model enables a comprehensive evaluation concerning the feasibility, acceptability and clinically meaningful deployment of digital health technologies across diverse populations grappling with substance-related health issues. Furthermore, it delineates strategies that facilitate the immediate implementation of interventions and the refinement of SUD treatment modalities by healthcare professionals. Given the rapid proliferation of digital health tools, the ensuing participant privacy concerns usher in unique ethical dilemmas. Consequently, it is essential to integrate ethical frameworks that instruct clinicians on navigating daily practice and

technology design, aiming to mitigate potential adverse effects on these populations, thereby preventing the aggravation of health disparities.

Furthermore, this study enhances its theoretical contributions by applying psycho socio-technical factors (clinicians' self-efficacy, clients ' equity and access, etc.) to understand the dynamic interactions between social systems and technological innovations within SUD treatment environments. This perspective facilitates a deeper analysis of how digital health tools are embedded within and influenced by existing social structures, norms, and practices, and vice versa. It encourages the examination of digital health technologies not merely as isolated interventions but as components of a larger ecosystem that includes end users' behaviour, policy regulations, and clients t engagement. This holistic view aids in identifying leverage points for systemic change, ensuring that digital health interventions are both technically sound and socially responsive, thereby maximising their potential to contribute positively to SUD treatment outcomes.

This interdisciplinary lens highlights the importance of considering a wide array of perspectives in designing, implementing, and evaluating digital health technologies, thereby enhancing their relevance, accessibility, and impact on individuals experiencing substance dependency.

Findings of this study offer a deep understanding of the core principles guiding digital health adoption, with a particular emphasis on the end user's viewpoint. Through a detailed exploration of the motivations compelling AOD practitioners to embrace and apply e-tools in the context of SUD, this research provides invaluable theoretical insights. Consequently, these insights significantly bolster the existing literature on digital health adoption and e-treatments for SUD.

The study builds on UTAUT model as a foundation theory for the study and extends it by integrating the digital health literature. Notably, all UTAUT constructs exhibited strong convergent and discriminant validity, reliability, and fit indices throughout every phase of the research. Such

outcomes reinforce the credibility of UTAUT as an effective predictor for the intention to adopt digital health. As a result, this research extends the current understanding of the UTAUT model and validates its use for Australian clinicians.

Subsequently, this research enhances the UTAUT framework by introducing six distinct constructs tailored to the SUD context: clinicians' self-efficacy, fear of COVID-19, client digital proficiency, the potential to establish a therapeutic alliance, trust, and privacy concerns. To the best of our knowledge, these variables have not been previously examined within the UTAUT model for clinicians' adoption of digital health. Acknowledging these factors paves the way for further research in digital health and equips AOD clinicians, treatment providers, and policymakers with insights into these intricate influences when leveraging e-tools. Furthermore, considering vulnerable populations, such as clients battling substance dependency, broadens the reach and applicability of digital health, solidifying its potential for expansive and impactful use.

Further, this study distinguishes itself from previous research. While earlier studies centred on clients, viewing them as the end-users, the current research is unique as it examines the perspectives of clinicians working in the field of substance dependency. These clinicians engage with clients and are seen as gatekeepers of digital health in their daily interactions.

7.2.2 Methodological contributions

This research adopted an exploratory sequential mixed-methods design characterised by its flexibility and collaborative approach. One significant outcome of this methodology was its ability to successfully develop and validate an instrument tailored for digital health adoption SUD treatment contexts in Australia. This framework can serve as a trustworthy tool for guiding future investigations into digital health use and acceptance in SUD. Furthermore, it can pave the way for effective digital health strategies for other chronic health conditions and mental health interventions, addressing the needs of a diverse range of practitioners.

7.2.2 Practical Implications

This research illuminates the dynamics of adopting e-health services in Australia, particularly spotlighting the pivotal factors that governed the adoption trajectory during the COVID-19 pandemic. Based on these findings, strategic solutions have been suggested to support and streamline the integration of digital health practices within the realm of SUD treatment. The outcomes of this research provide both a practical blueprint and a strategic roadmap for the holistic healthcare landscape. These findings, derived from rigorous investigation, hold the potential to substantially impact clinicians, clients, system and app developers, and the wider society. The primary intent is to bolster client engagement and pave the way for more efficient service models, thus addressing the substantial challenges of substance dependency in Australia. By proposing digitally-augmented care models, the research underscores the importance of enhancing accessibility, quality, safety, and efficiency in healthcare provision.

Beyond the confines of clinical practice, these insights resonate deeply with health administrators, decision-makers, and policy-formulating governmental bodies. The recommendations emanating from this study serve as a pivotal reference for IT departments and healthcare management. Their pertinence lies in refining digital health strategies, optimising service models, and ultimately lightening the load of substance dependency within the Australian context. This comprehensive approach, encapsulating both technological and human-centric perspectives, is designed to usher in an era of enhanced digital health care—a summary of practical implications outlined in Table 19.

Table 19 Summary of Practical Implications

Key factors	Practical implications
Privacy	For effective regulation and accountability, players must consider several key aspects: **Consent and Transparency**: It is essential to inform clients about the storage and usage of their data. Transparent communication builds trust and ensures that clients know their data rights. **Training and Awareness**: Continuous education about online risks and best practices for online safety is vital. Periodic training sessions can keep all stakeholders updated on potential security threats and the best measures to counteract them. **Strong Password Policies:** Implement robust password protocols to secure data further and prevent unauthorised access. **Client-Controlled Data Sharing**: Empower clients with control over who can access and share their data, allowing them the freedom to manage their own information. **Regular Check-ins on Privacy Comfort**: Periodically assess client comfort levels regarding privacy measures, ensuring they remain informed and satisfied with data protection procedures.
Trust in Digital Health	**Digital Health Toolkits**: Provide clinicians with a toolkit or reference guide for digital tools. This can be a quick-access guide for troubleshooting or understanding features. **E-Learning Modules**: Create e-learning modules on digital health tools and software that clinicians can access anytime, anywhere. This allows for flexibility and self-paced learning. **Peer Mentorship**: Encourage experienced clinicians to mentor their less tech-savvy peers. This kind of peer-to-peer interaction can often lead to faster understanding and adaptation. **Feedback Mechanisms**: Establish platforms or methods for clinicians to provide feedback on the digital tools they are using. This will ensure that issues are addressed promptly and provide insights into areas that require more training. **Implement a Rapid Response System:** In case of data breaches or security events, it is essential to have a dedicated response team in place to handle the situation swiftly and with full transparency. Ensure affected users are promptly notified and provided with details about the steps taken to address the issue.

Client Digital - Literacy	**Training Workshops**: Organise digital literacy workshops tailored to the needs of a diverse range of populations of clients, covering everything from basic device usage to advanced health data interpretation. **User-Friendly Design**: Ensure digital health platforms are designed with intuitive user interfaces, making them more accessible to all, including those with limited digital experience. **Provide Resources**: Offer guides, video tutorials, and FAQs on digital health platforms, addressing common concerns and challenges. **Establish Help Desks:** Offer dedicated helplines or chat services where clients can get real-time assistance with their digital health queries. **Feedback Mechanisms:** Regularly solicit feedback on the digital tools offered, making improvements based on clients' experiences and suggestions.
Clinicians' Self-Efficacy (SE)	**Skill Development Workshops**: Regularly organise training programs focusing on skill enhancement and the latest clinical practices. **Peer Feedback Systems and Supportive Work Environment:** Create platforms where clinicians can discuss cases, share insights, and provide feedback to each other. **Simulation and Role-Playing:** Use simulation tools and role-playing to allow clinicians to practice challenging scenarios and improve their skills in a risk-free environment. **Recognition and Reward**: Acknowledge and reward clinicians for their achievements, innovations, and exceptional patient care. **Access to Continued Learning**: Encourage and provide opportunities for clinicians to attend conferences, webinars, and workshops related to their field.

Possibility of Establishing a Therapeutical Alliance	Key skills for developing a strong therapeutic alliance when using digital health include but are not limited to risk management, maintaining boundaries, and creating a therapeutic space. **Active Listening:** Clinicians should listen without judgment and ensure they understand the patient's perspective. **Feedback Systems:** Regularly seek clients' feedback about their experience and make necessary adjustments. **Consistent Check-ins:** Periodically assess the health of the therapeutic alliance and address any emerging issues. **Empathy and Validation:** Make sure patients feel heard, and their feelings and experiences are validated. **Flexible Approach:** Be willing to adapt treatment plans based on patient feedback and changing circumstances. **Cultural Competence Training**: Ensure clinicians are trained to understand and respect cultural differences, which can be pivotal in forming a solid alliance with diverse patients. **Clarify Roles and Expectations:** At the onset of therapy, discuss the roles and responsibilities of both the therapist and the patient, setting the stage for a collaborative relationship.

This research provides essential insights for e-health technology designers, highlighting the challenges associated with developing and rolling out digital health tools, especially those focused-on client-centred interventions. This becomes even more critical when the target audience comprises stigmatised populations, as it is vital to ensure meaningful tool utilisation. As a result, a human-centred, integrated design approach should be at the forefront of digital health developer strategies. Engaging diverse populations of end-users and collaborating with in-field clinicians during the initial stages of digital health tool development to refine and enhance digital health solutions consistently. Such a partnership ensures that these tools are not merely modern interventions but are genuinely framed as solutions driving health equity.

For policymakers, it is vital to acknowledge the variance in treatment providers' perceptions of digital health. Such differences can significantly shape service delivery and, consequently, the client's care experience. If we assume treatment providers have strong trust in digital health and a high self-efficacy level, clients accessing treatment may be presented with multiple digital solutions and the most appropriate treatment solutions. Hence, it is necessary for policymakers to champion enhanced training access for AOD clinicians when designing services.

Additionally, considering the specific needs of clients and the resources at their disposal, a holistic strategy would highlight the establishment of legislative, regulatory and policy frameworks that emphasised humanising technology and endorsing client-centric care. Central to this approach is the advancement of digital health equity. Future research should delve into the influence of policy on digital health acceptance and usage.

7.3. Limitations and Future Research

Like all research endeavours, the present study was not without limitations. A salient limitation was the sample size: 18 participants in the qualitative phase and 120 in the quantitative phase. This restricts the generalizability of the findings.

A noteworthy constraint was that while a probability sampling method was employed, participation was inherently restricted to those who were accessible for interviews or those who responded to the online survey. Also, our primary recruitment strategy which was predominantly via LinkedIn. This inadvertently limited the inclusion of AOD professionals without LinkedIn profiles, potentially biasing our sample and not fully capturing the perspective of the broader AOD workforce. Consequently, future studies should be more inclusive by targeting diverse participants across different platforms and organisations, thus capturing richer insights from a broader range of clinicians.

Furthermore, the current research scope focused solely on clinicians actively working in the field. Expanding the focus in subsequent studies to include clients, caregivers, or technology providers could offer a holistic understanding of the topic.

This study examined and investigated ten leading factors influencing clinicians' willingness and decision to accept and adopt digital health. It would also be beneficial to consider additional variables, such as social and organisational factors (including workload, job security, leadership support, training, policies, and regulations), as well as technological elements like layout, interface, and culturally appropriate design. Exploring the interrelationships and impacts of these variables could shed light on the determinants affecting clinicians' adoption of digital health and could enhance the modified UTAUT model. the study's findings are significant, offering a unique examination of clinicians' perspectives at the individual level—a departure from previous research that primarily concentrated on clients/patients. This distinctive focus enhances our understanding of the field and underscores the study's contribution to advancing knowledge in this area.

7.4 Lessons Learned

This research has revealed several key lessons about the adoption of e-health interventions for substance use disorder treatment. Central to these lessons is the recognition that a human-cantered approach is critical when developing and implementing digital health tools. While digital solutions hold great promise for improving treatment delivery for this population, their success hinges on effectively addressing the diverse needs of all parties, including clinicians, clients, and health administrators and policy makers.

One of the primary lessons learned is the importance of privacy and client’s data protection in digital health adoption. Building user confidence in e-health systems requires more than just compliance with regulations; it demands a commitment to transparency, robust data security measures, and proactive engagement with clients to continually address their privacy concerns.

The research suggests that privacy considerations should be embedded into the core design and operational processes of digital health solutions, rather than being treated as an afterthought or mere regulatory requirement.

Moreover, the study emphasizes the critical role of digital health literacy among clients and clinicians. To maximize the benefits of digital interventions, they must be designed to be accessible and understandable to users from various backgrounds. Tailored digital literacy initiatives that accommodate various levels of user experience are essential for bridging gaps in accessibility and engagement particularly in vulnerable group such as people experiencing substance dependency. Implementing user-friendly designs, providing comprehensive support resources, and establishing continuous feedback mechanisms are practical strategies that can enhance client and clinician's competence and confidence in using digital health tools.

Clinician self-efficacy also emerged as a pivotal factor influencing the successful adoption of digital health tools. The study highlights the importance of ongoing training and professional development programs that address both technological and clinical skills. Such initiatives are vital for enhancing clinician comfort and proficiency with digital tools. Additionally, fostering a supportive work environment that promotes peer collaboration and feedback is crucial to ensure clinicians feel empowered and competent in utilizing these technologies effectively.

The research further underscores the need to preserve and strengthen the therapeutic alliance between clinicians and clients in digital environments. Maintaining a robust therapeutic relationship requires specific skills, such as active listening, empathy, and cultural competence, which are critical for effective care delivery. Digital health tools should be designed to support these relational elements, ensuring that the human connection in healthcare is not only maintained but also enhanced in digital settings.

Co- design or engaging diverse users and collaborating with clinicians during the initial stages of development ensures that digital health tools are both innovative and equitable, effectively

addressing the needs of all populations. This participatory approach helps to create solutions that are not just technologically advanced but also practically relevant and socially inclusive. These lessons serve as a guide for future efforts to integrate digital solutions into the broader healthcare landscape, ensuring they are both effective and equitable in improving client's outcomes.

7.5 Conclusion

Globally, there is a mounting crisis in substance dependency and its treatment, an urgency mirrored locally and across borders. Current service paradigms are grappling to fulfill the ever-expanding healthcare demands, positioning digital health technology as a beacon of potential resolution. However, the transformative capacity of this technology is tethered to its acceptance by treatment facilitators. The landscape of digital health adoption is intricate, shaped by myriad dimensions and influenced by many determinants.

This study develops a model for implementing digital health technologies in substance use disorder (SUD) treatment, emphasising participant privacy and equitable access to these technologies. It enhances the Unified Theory of Acceptance and Use of Technology (UTAUT) by adding SUD-specific factors like clinician self-efficacy and privacy concerns. The research underlines the importance of integrating technology within the specific concept of treatment environments and offers valuable insights into digital health adoption, ultimately aiming to improve SUD treatment outcomes.

APPENDICES

Appendix A: Summary of risk factors for COVID-19 in clients with drug dependency adopted from (López-Pelayo et al., 2020).

Substance-related factors	Contextual and pattern of use-related factors
• Claims have been made about nicotine having a protective effect, but a systematic review of 5 studies with 1358 participants indicated that smoking actually leads to worse COVID-19 outcomes. Additionally, a study involving 169 hospitals and 8910 patients found that the risk of dying from COVID-19 for current smokers was 79% higher compared to non-smokers. • Alcohol consumption, particularly in large amounts, can impair both the innate and adaptive immune systems, increasing susceptibility to infections like tuberculosis, hepatitis B and C, HIV/AIDS, and COVID-19,	Vaping and smoking can lead to lung injuries. • Some groups of drug users, such as those in jails or without homes, face difficulties accessing hand washing facilities, disinfectant wipes, and personal protective gear (PPE), and often live in overcrowded conditions. • Methamphetamine use can cause pulmonary hypertension. • Drug and alcohol use can weaken the immune system. • The stigma around drug and alcohol use can prevent people from seeking healthcare.

and exacerbating disease progression. • Heavy alcohol use is also a known risk factor for developing acute respiratory distress syndrome. • Regular use of cannabis has been linked to coughing and other respiratory issues.	• Sharing cigarettes, drinks, or needles is a risky behavior that can lead to infection with SARS-CoV-2. • Lockdown measures have affected the supply of illegal drugs, changing the behaviours of substance users.

Appendix B: Information Sheet for Interview

PARTICIPANT INFORMATION SHEET AND CONSENT FORM

Title: "Digital Health for Substance Use Disorder Treatment: Technology Acceptance by Alcohol and Drug Workers/ Social workers/Clinicians/Specialists

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1) Description of the study

This project will investigate the main factors that influence alcohol and other drug workers/ clinicians/specialists to use and accept digital health in substance use treatment, rehabilitation, and recovery settings. Digital health includes a range of technologies such as video counselling, mobile apps, website, email and wearable devices, that can support you or your clients for training, communications, referrals, assessment, or any other work/treatment-related activity. This project is supported by Flinders University, College of Science and Engineering.

2) Purpose of the study

This project aims to:

1. Gain an understanding of current practice in digital health for substance dependency treatment, rehabilitation, and recovery.
2. Identify the challenges facing alcohol and drug workers/clinicians/specialists in their use and acceptance of digital health, particularly in the post-COVID-19 era.
3. Identify the strategies that improve sustained use and acceptance of technology suitable for the substance use treatment field.

3) **What benefit will I gain from being involved in this study?**

Note that you may not directly benefit from participating, however sharing your everyday experience and views about technological tools is essential in developing more practical tools and make them accessible and suitable for you and your clients and create an integrated care system, particularly in the COVID-19 world and beyond.

4) **Recognition of Contribution**

If you would like to participate, you will be provided with a $50 Coles Group & Myer gift card to recognise your contribution and participation time. This gift card will be provided to you face-to-face on completion of the interview or online by emailing you the card number, expiry date and the 4-digit access code.

5) What will I be asked to do?

- Attend a one-on-one face-to-face or virtual interview with a researcher and share your experience and perspectives about using digital health for your work-related activity.
- The interview will be audio-recorded and take about 40 minutes.

6) Confidentiality and Privacy

Be assured that any information provided will be treated in the strictest confidence. None of the participants will be individually identifiable in future publications.

7) Are there any risks or discomforts if I am involved?

No, there are no risks, and this study will result in no disadvantage to you.

8) Withdrawal Rights

You may, without any penalty, decline to take part in this research study. If you decide to take part and later change your mind, you may, without any penalty, withdraw at any time without providing an explanation. Any data collected up to the point of your withdrawal will be securely destroyed. Data recorded during the interview may not be able to be destroyed. However, the data will not be used in this research study without your explicit consent.

9) Data Storage

The information collected may be stored securely on a password protected computer and/or Flinders University server throughout the study. Any identifiable data will be de-identified for data storage purposes unless indicated otherwise. All data will be securely transferred to and stored at Flinders University for at least five years after publication of the results. Following the required data storage period, all data will be securely destroyed according to university protocols.

10) How will I receive feedback?

On project completion, a summary of the research outcomes will be provided to you via email.

11) Queries and Concerns

Queries or concerns regarding the research can be directed to the research team. If you have any complaints or reservations about the ethical conduct of this study, you may contact the Flinders University's Research Ethics & Compliance Office team via telephone 08 8201 3116 or email human.researchethics@flinders.edu.au.

12) Ethics Committee Approval

The project has been approved by Flinders University's Human Research Ethics Committee (465).

CONSENT FORM

Consent Statement

☐ I have read and understood the information about the research, and I understand I am being asked to provide informed consent to participate in this research study. I understand that I can contact the research team if I have further questions about this research study.

☐ I am not aware of any condition that would prevent my participation, and I agree to participate in this project.

☐ I understand that I am free to withdraw at any time during the study.

☐ I understand that I can contact the Flinders University's Research Ethics & Compliance Office if I have any complaints or reservations about the ethical conduct of this study.

☐ I understand that my involvement is confidential, and that the information collected may be published. I understand that I will not be identified in any research products.

I further consent to *delete/add boxes as require.*

☐ participating in an interview

☐ having my information audio recorded

☐ my data and information being used in this project and other related projects for an extended period of time (no more than 5 years after the publication of the data)

Signed:

Name:

Date:

Thank you.

Appendix C: Qualitative Interview Questions Guide

1. Tell me about your current position? Tell me about your day-to-day role and the type of clients you see?
2. How long have you been working in the substance treatment field?
3. Would you please tell me if you are using any digital health technology for your work-related activities (for your clients or yourself) and which ones? What did you use it for? Is that typically how you use it? When and why did you start using it?
4. What benefits have you experienced from using it? Or what future benefits would you expect?

5. What challenges, if any, have you had related to your digital devices in your job (in your job if you use them at work?
6. Are any of your colleagues using this tool?
7. Would you recommend it to others? Why? Why not?
8. How easy is it for you to use e- tools? Have you been to any recent training for e-tools?
9. When was the last time that you had difficulty with a computer or your email? Example? How was it fixed?
10. Do you know anyone in your organisation that cannot use e-tools? Email, computer?
11. Has there been a change in attitudes towards e-Tools in your workplace before and after COVID-19? What is the difference regarding e- tools?
12. What percentage of your clients have reliable internet/computer/smartphone? Are they confident to use smartphones and the internet? Any issue?
13. What is your main concern connecting with your clients in the online space?
14. What is your work suburb/ Postcode? Have you ever worked in any other location? Any differences?
15. What is your educational background and training?
16. How old are you?

Appendix D Questionnaire for Quantitative Study

Survey Questionnaire

Start of Block: Block 1- Personal Information

Gender

- ○ Male
- ○ Female
- ○ Non-binary/third gender
- ○ I prefer not to say

Age

- ○ 20 or under
- ○ 21-30
- ○ 31-40
- ○ 41-50
- ○ 51+

Education Level:

- ○ Diploma
- ○ Bachelor's degree
- ○ Post-graduate degree
- ○ Other

What is your postcode?

_____

End of Block: Block 1- Personal Information

Start of Block: Block 2- User Behaviour

Behavioural intention (BI)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- I intend to use digital health in the future	○	○	○	○	○

How often do you use the following digital health technologies?

	Never/Rarely	Two times a month	Two times a week	Several times a day
1- The phone call /Email	○	○	○	○
2- Mobile app related to substance dependency	○	○	○	○
3- Video conference (Skype, Zoom, WhatsApp&....)	○	○	○	○
4- My organization's software	○	○	○	○
5-Other (Big data, Cloud computing, Heath sensing)	○	○	○	○

End of Block: Block 2- User Behaviour

Start of Block: Block 3- UTAT

Performance expectancy (PE)

	Strongly disagree	disagree	Neutral	Agree	Strongly	Strongly agree
1- Using digital health enables me to accomplish my duties more quickly and efficiently.	○	○	○	○	○	○
2- Using digital health would help me to save time.	○	○	○	○	○	○
3- Using digital health increases the quality of addiction treatment services.	○	○	○	○	○	○

Effort expectancy (EE)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- Learning to work with digital health is easy.	○	○	○	○	○
2- Using digital health is easy.	○	○	○	○	○
3- It is easy for me to become skillful at using digital health.	○	○	○	○	○

Social influence (SI)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- People who are important to me think I should use digital health.	○	○	○	○	○
2- People who influence my behaviour think I should use digital health.	○	○	○	○	○
3- I would use digital health if my friends and colleagues used them.	○	○	○	○	○
4- In general, I have been supported in using digital health.	○	○	○	○	○

Facilitating conditions (FC)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- I have the resources necessary to use digital health (WIFI/laptop/computer).	○	○	○	○	○
2- I have the knowledge necessary to use digital health (Computer knowledge).	○	○	○	○	○
3- I think using digital health fits well with my work/position responsibilities.	○	○	○	○	○
4- A specific person (or group) is available for assistance with digital health difficulties (IT support).	○	○	○	○	○

End of Block: Block 3- UTAT

Start of Block: Block 4- SUD Constructs

Trust

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- I usually trust digital health until there is a reason not to.	○	○	○	○	○
2- For the most part, I distrust digital health.	○	○	○	○	○
3- In general, I would rely on digital health to assist me.	○	○	○	○	○
4- My tendency to trust digital health is high.	○	○	○	○	○
5- I will likely trust digital health even when I know little about it.	○	○	○	○	○

Privacy

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- It bothers my clients when I ask them about their personal information.	○	○	○	○	○
2- Some of my clients are concerned that I will collect too much personal information.	○	○	○	○	○
3- Some of my clients are concerned that unauthorized people may access their personal information.	○	○	○	○	○
4- Some of my clients are concerned that my organization or I may keep their personal information in a non-accurate manner.	○	○	○	○	○

Click to write the question text

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- I could use any new digital health tool if no one was around to tell me what to do.	○	○	○	○	○
2- I could use any new digital health tool if I could call someone for help if I got stuck.	○	○	○	○	○
3- I could use any new digital health tool if I had more time to become familiar with it.	○	○	○	○	○
4- I could use any new digital health tool if I had just the built-in help facility.	○	○	○	○	○
5- I could use any new digital health tool if someone showed me how to use it first.	○	○	○	○	○

Fear of COVID-19(FC19)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- I am very afraid of COVID-19	○	○	○	○	○
2- It makes me uncomfortable to think about COVID-19.	○	○	○	○	○
3- I become nervous or anxious when watching news and stories about COVID-19.	○	○	○	○	○
4- I still have some concerns about socializing in large public events, public transport or crowded places due to COVID-19	○	○	○	○	○

Digital Literacy

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- My clients know how to find helpful health resources on the Internet.	○	○	○	○	○
2- My clients know what health resources are available on the Internet.	○	○	○	○	○
3- My clients have the skills they need to evaluate the health resources they find on the Internet.	○	○	○	○	○
4- My clients feel confident in using information from the Internet to make health decisions.	○	○	○	○	○

Digital accessibility Barriers

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- My clients cannot afford to have a smartphone.	○	○	○	○	○
2- My clients do not have the money to get an Internet connection.	○	○	○	○	○

Therapeutic Alliance

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1- My online session is as supportive as my face-to-face session.	○	○	○	○	○
2- My clients and I agree about how to work together in online sessions.	○	○	○	○	○
3- I am confident in my abilities during my online therapist sessions.	○	○	○	○	○

End of Block: Block 4- SUD Constructs

Appendix E: Ethics Approval Letters

9 September 2021

HUMAN ETHICS LOW RISK PANEL

APPROVAL NOTICE

Dear Ms. Lida Shams,

The below proposed project has been **approved** on the basis of the information contained in the application and its attachments.

Project No: 4659

Project Title: "Digital Health for Substance Use Disorder Treatment: Technology Acceptance by Alcohol and Drug Workers/ Social

workers/Clinicians/Specialists"

Primary Researcher: Ms Lida Shams

Approval Date: 09/09/2021

Expiry Date: 01/04/2023

Please note: *Due to the current COVID-19 situation, researchers are strongly advised to develop a research design that aligns with the University's*

COVID-19 research protocol involving human studies. Where possible, avoid face-to-face testing and consider rescheduling face-to-face testing or

undertaking alternative distance/online data or interview collection means. For further information, please go to https://staff.flinders.edu.au/coronavirusinformation/

research-updates.

RESPONSIBILITIES OF RESEARCHERS AND SUPERVISORS

1. Participant Documentation

Please note that it is the responsibility of researchers and supervisors, in the case of student projects, to ensure that:

All participant documents are checked for spelling, grammatical, numbering and formatting errors. The Committee does not accept

any responsibility for the above-mentioned errors.

the Flinders University logo is included on all participant documentation (e.g., letters of Introduction, information Sheets, consent

forms, debriefing information and questionnaires – with the exception of purchased research tools) and the current Flinders

University letterhead is included in the header of all letters of introduction. The Flinders University international logo/letterhead should

be used and documentation should contain international dialing codes for all telephone and fax numbers listed for all research to be

conducted overseas.

2. Annual Progress / Final Reports

In order to comply with the monitoring requirements of the *National Statement on Ethical Conduct in Human Research 2007 (updated*

2018) an annual progress report must be submitted each year on the approval anniversary date for the duration of the ethics approval

using the HREC Annual/Final Report Form available online via the Research Now Ethics & Biosafety system.

Please note that no data collection can be undertaken after the ethics approval expiry date listed at the top of this notice. If data is

collected after expiry, it will not be covered in terms of ethics. It is the responsibility of the researcher to ensure that annual progress reports

are submitted on time; and that no data is collected after ethics has expired.

If the project is completed *before* ethics approval has expired, please ensure a final report is submitted immediately. If ethics approval for

your project expires please either submit (1) a final report; or (2) an extension of time request (using the HREC Modification Form).

For student projects, the Low-Risk Panel recommends that current ethics approval is maintained until a student's thesis has been

submitted, assessed and finalised. This is to protect the student in the event that reviewers recommend that additional data be collected

from participants.

3. Modifications to Project

Modifications to the project must not proceed until approval has been obtained from the Ethics Committee. Such proposed changes /

modifications include:

change of project title;

change to research team (e.g., additions, removals, researchers and supervisors)

changes to research objectives;

changes to research protocol;

changes to participant recruitment methods;

changes / additions to source(s) of participants;

changes of procedures used to seek informed consent;

changes to reimbursements provided to participants;

changes to information / documents to be given to potential participants;

changes to research tools (e.g., survey, interview questions, focus group questions etc);

extensions of time (i.e. to extend the period of ethics approval past current expiry date).

To notify the Committee of any proposed modifications to the project please submit a Modification Request Form available online via the

ResearchNow Ethics & Biosafety system. Please note that extension of time requests should be submitted prior to the Ethics Approval

Expiry Date listed on this notice.

4. Adverse Events and/or Complaints

Researchers should advise the Executive Officer of the Human Research Ethics Committee on at human.researchethics@flinders.edu.au

immediately if:

any complaints regarding the research are received;

a serious or unexpected adverse event occurs that effects participants;

an unforeseen event occurs that may affect the ethical acceptability of the project.

Yours sincerely,

Hendryk Flaegel

on behalf of

Human Ethics Low Risk Panel

Research Development and Support

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REFERENCE

Abuse, S. (2018). Mental Health Services Administration. 2016 National survey on drug use and health: detailed tables. *Substance Abuse and Mental Health Services Administration*.

Adjekum, A., Blasimme, A., & Vayena, E. (2018). Elements of Trust in Digital Health Systems: Scoping Review. *J Med Internet Res, 20*(12), e11254. doi:10.2196/11254

Agarwal, R., & Prasad, J. (2000). A field study of the adoption of software process innovations by information systems professionals. *IEEE Transactions on Engineering Management, 47*(3), 295-308. doi:10.1109/17.865899

Agnew-Davies, R., Stiles, W. B., Hardy, G. E., Barkham, M., & Shapiro, D. A. (1998). Alliance structure assessed by the Agnew Relationship Measure (ARM). *British Journal of Clinical Psychology, 37*(2), 155-172.

Ahmad, S. Z., & Khalid, K. (2017). The adoption of M-government services from the user's perspectives: Empirical evidence from the United Arab Emirates. *International journal of information management, 37*(5), 367-379.

Ahmed, T., Rizvi, S. J. R., Rasheed, S., Iqbal, M., Bhuiya, A., Standing, H., . . . Waldman, L. (2020). Digital health and inequalities in access to health services in Bangladesh: mixed methods study. *JMIR mHealth and uHealth, 8*(7), e16473.

Ahorsu, D. K., Lin, C.-Y., Imani, V., Saffari, M., Griffiths, M. D., & Pakpour, A. H. (2020). The fear of COVID-19 scale: development and initial validation. *International Journal of Mental Health and Addiction*, 1-9.

Ahorsu, D. K., Lin, C.-Y., Imani, V., Saffari, M., Griffiths, M. D., & Pakpour, A. H. (2022). The Fear of COVID-19 Scale: Development and Initial Validation. *International Journal of Mental Health and Addiction, 20*(3), 1537-1545. doi:10.1007/s11469-020-00270-8

AIHW. (2020). Australian Institute of Health and Welfare National Drug Strategy Household Survey 2019. Drug Statistics series no. 32. PHE 270. Canberra AIHW.

AIHW. (2022a). *Alcohol and Other Drug Treatment Services in Australia 2021-2022*: Australian Institute of Health and Welfare.

AIHW. (2022b). Australian Institute of Health

Welfare. Alcohol and other drug treatment services in Australia annual report. Retrieved from https://www.aihw.gov.au/reports/alcohol-other-drug-treatment-services/alcohol-other-drug-treatment-services-australia

AIHW. (2023). Australian Institute of Health and Welfare. Alcohol and other drug treatment services in Australia: early insights. Retrieved from https://www.aihw.gov.au/reports/alcohol-other-drug-treatment-services/alcohol-other-drug-treatment-services-aus

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211.

Ajzen, I., & Fishbein, M. (1975a). A Bayesian analysis of attribution processes. *Psychological Bulletin, 82*, 261-277. doi:10.1037/h0076477

Ajzen, I., & Fishbein, M. (1975b). A Bayesian analysis of attribution processes. *Psychological Bulletin, 82*(2), 261-277. doi:10.1037/h0076477

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological Bulletin, 84*(5), 888-918. doi:10.1037/0033-2909.84.5.888

Ajzen&Fishbein. (1980). Theory of reasoned action (TRA) in information seeking behavior and technology adoption: theories and trends. *ed: IGI Global*.

Akhtar, N., Rahman, S., Sadia, H., & Perwej, Y. (2021). A Holistic Analysis of Medical Internet of Things (MIoT). *Journal of Information and Computational Science, 11*(4), 209-222. Retrieved from https://hal.science/hal-03226578

Al-Adawi, Z., Yousafzai, S., & Pallister, J. (2005). *Conceptual model of citizen adoption of e-government.* Paper presented at the The second international conference on innovations in information technology.

Alam, M. Z., Hu, W., Hoque, M. R., & Kaium, M. A. (2020). Adoption intention and usage behavior of mHealth services in Bangladesh and China: A cross-country analysis. *International Journal of Pharmaceutical and Healthcare Marketing, 14*(1), 37-60.

Alazzam, M. B., Basari, A. S. H., Sibghatullah, A. S., Ibrahim, Y. M., Ramli, M. R., & Naim, M. H. (2016). Trust in stored data in EHRs acceptance of medical staff: using UTAUT2. *International Journal of Applied Engineering Research, 11*(4), 2737-2748.

Alhiary, E. M. (2023). Adopting electronic healthcare services during COVID-19 and the nations responding: evidence from Jordan. *International Journal of Procurement Management, 16*(1), 136-150.

Aljedaani, B., & Babar, M. A. (2021). Challenges With Developing Secure Mobile Health Applications: Systematic Review. *JMIR Mhealth Uhealth, 9*(6), e15654. doi:10.2196/15654

Allnutt, S. H., Ogloff, J. R., Adams, J., O'Driscoll, C., Daffern, M., Carroll, A., . . . Chaplow, D. (2013). Managing aggression and violence: the clinician's role in contemporary mental health care. *Australian & New Zealand Journal of Psychiatry, 47*(8), 728-736.

Almutairi, A. M. M. (2021). Principles of drug addiction treatment. *Int J Med Dev Ctries, 5*(2), 1523-1527. doi:

https://doi.org/10.24911/IJMDC.51-1609883100

Alsahafi, Y. A., Gay, V., & Khwaji, A. A. (2022). Factors affecting the acceptance of integrated electronic personal health records in Saudi Arabia: The impact of e-health literacy. *Health Information Management Journal, 51*(2), 98-109.

Alshammari, W. M. G., Alshammari, F. M. M., & Alshammry, F. M. M. (2021). Factors Influencing the Adoption of E-Health Management among Saudi Citizens with Moderating Role of E-Health Literacy. *Information Management and Business Review, 13*(3 (I)), 47-61.

Alshenqeeti, H. (2014). Interviewing as a data collection method: A critical review. *English linguistics research, 3*(1), 39-45.

Altman, D. G. (1990). *Practical statistics for medical research*: CRC press.

Alyoussef, I. Y. (2023). Acceptance of e-learning in higher education: The role of task-technology fit with the information systems success model. *Heliyon, 9*(3). doi:10.1016/j.heliyon.2023.e13751

Anderson, T. W., & Darling, D. A. (1954). A test of goodness of fit. *Journal of the American statistical Association, 49*(268), 765-769.

Andy, F. (2005). Discovering statistics using SPSS: And sex and drugs and rock "n" roll. In: London: Sage.

Anton, M. T., & Jones, D. J. (2017). Adoption of technology-enhanced treatments: Conceptual and practical considerations. *Clinical Psychology: Science and Practice, 24*(3), 223.

Arbuckle, J. L. (2011). IBM SPSS Amos 20 user's guide. *Amos development corporation, SPSS Inc*, 226-229.

Areàn, P. A., Hoa Ly, K., & Andersson, G. (2022). Mobile technology for mental health assessment. *Dialogues in Clinical Neuroscience, 18*(2), 163-169. doi:10.31887/DCNS.2016.18.2/parean

Arechar, A. A., Gächter, S., & Molleman, L. (2018). Conducting interactive experiments online. *Experimental Economics, 21*(1), 99-131. doi:10.1007/s10683-017-9527-2

Ashford, R. D., Bergman, B. G., Kelly, J. F., & Curtis, B. (2020). Systematic review: Digital recovery support services used to support substance use disorder recovery. *Human Behavior and Emerging Technologies, 2*(1), 18-32. doi:https://doi.org/10.1002/hbe2.148

Asvinigita, L. R. M., Piartrini, P. S., Suprapti, N. W. S., & Widagda, I. (2022). Application of Theory of Reasoned Action (TRA) to Explain Continued Intention to Adopt (CIA) MHealth Services. *Webology, 19*(1), 4952-4966. doi:10.14704/WEB/V19I1/WEB19332

Aukstakalnis, S. (2016). *Practical augmented reality: A guide to the technologies, applications, and human factors for AR and VR*: Addison-Wesley Professional.

Avgousti, K. (2013). Research philosophy, methodology, quantitative and qualitative methods. *The Cyprus Journal of Sciences, 11*, 33.

Baker, J. (2012). The technology–organization–environment framework. *Information Systems Theory: Explaining and Predicting Our Digital Society, Vol. 1*, 231-245.

Bakken, S. A., & Demant, J. J. (2019). Sellers' risk perceptions in public and private social media drug markets. *International Journal of Drug Policy, 73*, 255-262. doi:https://doi.org/10.1016/j.drugpo.2019.03.009

Balakrishnan, R., Gopichandran, V., Chaturvedi, S., Chatterjee, R., Mahapatra, T., & Chaudhuri, I. (2016). Continuum of Care Services for Maternal and Child Health using mobile technology – a health system strengthening strategy in low and middle income countries. *BMC Medical Informatics and Decision Making, 16*(1), 84. doi:10.1186/s12911-016-0326-z

Balapour, A., Reychav, I., Sabherwal, R., & Azuri, J. (2019). Mobile technology identity and self-efficacy: Implications for the adoption of clinically supported mobile health apps. *International Journal of Information Management, 49*, 58-68. doi:https://doi.org/10.1016/j.ijinfomgt.2019.03.005

Bandura, A. (1986). The explanatory and predictive scope of self-efficacy theory. *Journal of social and clinical psychology, 4*(3), 359-373.

Barak, A., Klein, B., & Proudfoot, J. G. (2009). Defining Internet-Supported Therapeutic Interventions. *Annals of Behavioral Medicine, 38*(1), 4-17. doi:10.1007/s12160-009-9130-7

Barker, G. G., & Barker, E. E. (2022). Online therapy: lessons learned from the COVID-19 health crisis. *British Journal of Guidance & Counselling, 50*(1), 66-81. doi:10.1080/03069885.2021.1889462

Barrett, P. (2007). Structural equation modelling: Adjudging model fit. *Personality and Individual differences, 42*(5), 815-824.

Barrowclough, C., Marshall, M., Gregg, L., Fitzsimmons, M., Tomenson, B., Warburton, J., & Lobban, F. (2014). A phase-specific psychological therapy for people with problematic cannabis use following a first episode of psychosis: a randomized controlled trial. *Psychological Medicine, 44*(13), 2749-2761. doi:10.1017/S0033291714000208

Batra, S., Baker, R. A., Wang, T., Forma, F., DiBiasi, F., & Peters-Strickland, T. (2017). Digital health technology for use in patients with serious mental illness: a systematic review of the literature. *Medical Devices: Evidence and Research, 10*(null), 237-251. doi:10.2147/MDER.S144158

Baudendistel, I., Winkler, E., Kamradt, M., Längst, G., Eckrich, F., Heinze, O., . . . Ose, D. (2015). Personal Electronic Health Records: Understanding User Requirements and Needs in Chronic Cancer Care. *J Med Internet Res, 17*(5), e121. doi:10.2196/jmir.3884

Bauer, A. M., Thielke, S. M., Katon, W., Unützer, J., & Areán, P. (2014). Aligning health information technologies with effective service delivery models to improve chronic disease care. *Preventive Medicine, 66*, 167-172. doi:https://doi.org/10.1016/j.ypmed.2014.06.017

Beldad, A. D., & Hegner, S. M. (2018). Expanding the technology acceptance model with the inclusion of trust, social influence, and health valuation to determine the predictors of German users' willingness to continue using a fitness app: A structural equation modeling approach. *International Journal of Human–Computer Interaction, 34*(9), 882-893.

Benbasat, I., & Wang, W. (2005). Trust In and Adoption of Online Recommendation Agents. *J. AIS, 6*. doi:10.17705/1jais.00065

Bennett, S., Maton, K., & Kervin, L. (2008). The 'digital natives' debate: A critical review of the evidence. *British Journal of Educational Technology, 39*(5), 775-786. doi:https://doi.org/10.1111/j.1467-8535.2007.00793.x

Berger, T. (2017). The therapeutic alliance in internet interventions: A narrative review and suggestions for future research. *Psychotherapy Research, 27*(5), 511-524. doi:10.1080/10503307.2015.1119908

Bergin, M. (2011). NVivo 8 and consistency in data analysis: Reflecting on the use of a qualitative data analysis program. *Nurse researcher, 18*(3). doi:10.7748/nr2011.04.18.3.6.c8457

Berry, N., Bucci, S., & Lobban, F. (2017). Use of the Internet and Mobile Phones for Self-Management of Severe Mental Health Problems: Qualitative Study of Staff Views. *JMIR Ment Health, 4*(4), e52. doi:10.2196/mental.8311

Berzin, S. C., Singer, J., & Chan, C. (2015). Practice innovation through technology in the digital age: A grand challenge for social work. *American Academy of Social Work & Social Welfare, 12*, 3-21.

Bhatia, R. (2021). Telehealth and COVID-19: Using technology to accelerate the curve on access and quality healthcare for citizens in India. *Technology in society, 64*, 101465.

Bhatt, S., Singh, G., & Aslam, W. (2023). Extension of technology acceptance model: considering cultural values and expectations with special reference to telemedicine in India. *International Journal of Economics and Business Research, 25*(2), 270-291.

Birks, M., Coyle, M., Porter, J., & Mills, J. (2011). Perceptions of hand hygiene amongst health care workers in Sibu, East Malaysia. *International Journal of Infection Control, 8*, 10-13.

Bisen, S. S., & Deshpande, Y. (2018). The Impact of the Internet in twenty-first century addictions: An overview. *Psychological, Social, and Cultural Aspects of Internet Addiction*, 1-19. doi: 10.4018/978-1-5225-3477-8.ch001

Björgvinsson, E., Ehn, P., & Hillgren, P.-A. (2010). *Participatory design and "democratizing innovation"*. Paper presented at the Proceedings of the 11th Biennial Participatory Design Conference, Sydney, Australia. https://doi.org/10.1145/1900441.1900448

Bliuc, A.-M., Best, D., Iqbal, M., & Upton, K. (2017). Building addiction recovery capital through online participation in a recovery community. *Social Science & Medicine, 193*, 110-117. doi:https://doi.org/10.1016/j.socscimed.2017.09.050

Bogdan, R., & Biklen, S. K. (1997). *Qualitative research for education*: Allyn & Bacon Boston, MA.

Bokolo, A. J. (2021). Exploring the adoption of telemedicine and virtual software for care of outpatients during and after COVID-19 pandemic. *Irish Journal of Medical Science (1971-), 190*(1), 1-10.

Bomil, S., & Ingoo, H. (2003). The Impact of Customer Trust and Perception of Security Control on the Acceptance of Electronic Commerce. *International Journal of Electronic Commerce, 7*(3), 135-161. doi:10.1080/10864415.2003.11044270

Bonny-Noach, H., Gold, D., & Caduri, A. Applying the theory of planned behavior to predict online addiction treatment intention. *Journal of Addictive Diseases*, 1-8. doi:10.1080/10550887.2023.2230834

Boontarig, W., Chutimaskul, W., Chongsuphajaisiddhi, V., & Papasratorn, B. (2012). *Factors influencing the Thai elderly intention to use smartphone for e-Health services.* Paper presented at the 2012 IEEE symposium on humanities, science and engineering research.

Bowling, A. (2002). *Research methods in health: investigating health and health services. 2nd edition*.

Bozdağ, N., & Çuhadar, D. (2022). Internalized stigma, self-efficacy and treatment motivation in patients with substance use disorders. *Journal of Substance Use, 27*(2), 174-180. doi:https://doi.org/10.1080/14659891.2021.1916846

Breslau, J., & Engel, C. C. (2015). Information and Communication Technologies in Behavioral Health.

Brown, S. E., Krishnan, A., Ranjit, Y. S., Marcus, R., & Altice, F. L. (2020). Assessing mobile health feasibility and acceptability among HIV-infected cocaine users and their healthcare providers: guidance for implementing an intervention. *Mhealth, 6*, 4. doi:10.21037/mhealth.2019.09.12

Bryman, A., Becker, S., & Sempik, J. (2008). Quality Criteria for Quantitative, Qualitative and Mixed Methods Research: A View from Social Policy. *International Journal of Social Research Methodology, 11*(4), 261-276. doi:10.1080/13645570701401644

Bucci, S., Schwannauer, M., & Berry, N. (2019). The digital revolution and its impact on mental health care. *Psychology and Psychotherapy: Theory, Research and Practice, 92*(2), 277-297.

Bucerius, J., Gummert, J. F., Borger, M. A., Walther, T., Doll, N., Onnasch, J. F., . . . Mohr, F. W. (2003). Stroke after cardiac surgery: a risk factor analysis of 16,184 consecutive adult patients. *The Annals of thoracic surgery, 75*(2), 472-478.

Campbell, A. M. (2020). An increasing risk of family violence during the Covid-19 pandemic: Strengthening community collaborations to save lives. *Forensic Science International: Reports, 2*, 100089. doi:https://doi.org/10.1016/j.fsir.2020.100089

Campo, M., & Tayton, S. (2015). *Domestic and family violence in regional, rural and remote communities*: Australian Institute of Family Studies.

Canton, H. (2021). United Nations Office on Drugs and Crime—UNODC. In *The Europa Directory of International Organizations 2021* (pp. 240-244): Routledge.

Carah, N., Meurk, C., & Hall, W. (2015). Profiling Hello Sunday Morning: Who are the participants? *International Journal of Drug Policy, 26*(2), 214-216. doi:https://doi.org/10.1016/j.drugpo.2014.07.019

Castaneda, C., Nalley, K., Mannion, C., Bhattacharyya, P., Blake, P., Pecora, A., . . . Suh, K. S. (2015). Clinical decision support systems for improving diagnostic accuracy and achieving precision medicine. *Journal of Clinical Bioinformatics, 5*(1), 4. doi:10.1186/s13336-015-0019-3

Chan, C., & Holosko, M. J. (2016). A review of information and communication technology enhanced social work interventions. *Research on Social Work Practice, 26*(1), 88-100. doi:DOI: 10.1177/1049731515578884

Chan, S., Markoulakis, R., & Levitt, A. (2023). Predictors of barriers to accessing youth mental health and/or addiction care. *J Can Acad Child Adolesc Psychiatry, 32*(1), 27-37.

Chang, Y.-T., Chao, C.-M., Yu, C.-W., & Lin, F.-C. (2021). Extending the Utility of UTAUT2 for Hospital Patients' Adoption of Medical Apps: Moderating Effects of e-Health Literacy. *Mobile Information Systems, 2021*, 8882317. doi:10.1155/2021/8882317

Chau, P. Y. K., & Hu, P. J. (2002). Examining a Model of Information Technology Acceptance by Individual Professionals: An Exploratory Study. *Journal of Management Information Systems, 18*(4), 191-229. doi:10.1080/07421222.2002.11045699

Check, J., & Schutt, R. K. (2011). *Research methods in education*: Sage publications.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural equation modeling: a multidisciplinary journal, 14*(3), 464-504.

Chen, L.-d., Gillenson, M. L., & Sherrell, D. L. (2002). Enticing online consumers: an extended technology acceptance perspective. *Information & Management, 39*(8), 705-719. doi:https://doi.org/10.1016/S0378-7206(01)00127-6

Chipeva, P., Cruz-Jesus, F., Oliveira, T., & Irani, Z. (2018). Digital divide at individual level: Evidence for Eastern and Western European countries. *Government Information Quarterly, 35*(3), 460-479. doi:https://doi.org/10.1016/j.giq.2018.06.003

Choun, D. L., & Petre, A. (2022). *Digital health and patient data: Empowering patients in the healthcare ecosystem*: CRC Press.

Cimperman, M., Makovec Brenčič, M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior—applying an Extended UTAUT model. *International Journal of Medical Informatics, 90*, 22-31. doi:https://doi.org/10.1016/j.ijmedinf.2016.03.002

Clipper, B. (2020). The Influence of the COVID-19 Pandemic on Technology: Adoption in Health Care. *Nurse Leader, 18*(5), 500-503. doi:https://doi.org/10.1016/j.mnl.2020.06.008

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS quarterly*, 189-211.

Cooper, D. R., Schindler, P. S., Cooper, D. R., & Schindler, P. S. (2006). *Marketing research*: McGraw-Hill/Irwin New York.

Coppock, A., & McClellan, O. A. (2019). Validating the demographic, political, psychological, and experimental results obtained from a new source of online survey respondents. *Research & Politics, 6*(1), 2053168018822174.

Creswell. (2007). *Qualitative inquiry and research design: Choosing among five approaches, 2nd ed*. Thousand Oaks, CA, US: Sage Publications, Inc.

Creswell, & Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches*: Sage publications.

Creswell, J. W. (2011). Controversies in mixed methods research. *The Sage handbook of qualitative research, 4*(1), 269-284.

Cunningham, J. A., Kypri, K., & McCambridge, J. (2011). The use of emerging technologies in alcohol treatment. *Alcohol Research & Health, 33*(4), 320.

D'Arcey, J. N., Tackaberry-Giddens, L., Junaid, S., Zhou, W., Quilty, L., Sloan, M., & Kidd, S. A. (2024). Co-Design of a Digital Health Tool for Use by Individuals With Opioid Use Disorder: App4Independence (A4i-O). *Substance Use & Addiction Journal*, 29767342241258915. doi:10.1177/29767342241258915

Daley, D. C., & Feit, M. D. (2013). The Many Roles of Social Workers in the Prevention and Treatment of Alcohol and Drug Addiction: A Major Health and Social Problem Affecting Individuals, Families, and Society. *Social Work in Public Health, 28*(3-4), 159-164. doi:10.1080/19371918.2013.758960

Damanpour, F. (1996). Organizational Complexity and Innovation: Developing and Testing Multiple Contingency Models. *Management Science, 42*(5), 693-716. doi:10.1287/mnsc.42.5.693

Dasgupta, A. (2017). 4 - Combined alcohol and drug abuse: A potentially deadly mix. In A. Dasgupta (Ed.), *Alcohol, Drugs, Genes and the Clinical Laboratory* (pp. 75-88): Academic Press.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results.* Massachusetts Institute of Technology,

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.

De Pourcq, K., Gemmel, P., Devis, B., Van Ooteghem, J., De Caluwé, T., & Trybou, J. (2019). A three-step methodology for process-oriented performance: how to enhance automated data collection in healthcare. *Informatics for Health and Social Care, 44*(3), 313-325. doi:10.1080/17538157.2018.1496087

De Vaus, D., & de Vaus, D. (2013). *Surveys in social research*: Routledge.

Deneke, E., Knepper, C., Green, B. A., & Carnes, P. J. (2015). Comparative Study of Three Levels of Care in a Substance Use Disorder Inpatient Facility on Risk for Sexual Addiction. *Sexual Addiction & Compulsivity, 22*(2), 109-125. doi:10.1080/10720162.2014.979382

Deokar, A. V., & Sarnikar, S. (2016). Understanding process change management in electronic health record implementations. *Information Systems and e-Business Management, 14*(4), 733-766. doi:10.1007/s10257-014-0250-7

Dhagarra, D., Goswami, M., & Kumar, G. (2020). Impact of trust and privacy concerns on technology acceptance in healthcare: an Indian perspective. *International journal of medical informatics, 141*, 104164.

Dickens, C., Lambert, B. L., Cromwell, T., & Piano, M. R. (2013). Nurse Overestimation of Patients' Health Literacy. *Journal of Health Communication, 18*(sup1), 62-69. doi:10.1080/10810730.2013.825670

Digital. (2024, 10 FEBRUARY 2024). DIGITAL 2024: GLOBAL OVERVIEW REPORT Retrieved from https://datareportal.com/reports/digital-2023-global-overview-report

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method*: John Wiley & Sons.

Dillon, A., & Morris, M. G. (1996). User acceptance of new information technology: theories and models.

Dimitrov, D. V. (2016). Medical Internet of Things and Big Data in Healthcare. *hir, 22*(3), 156-163. doi:10.4258/hir.2016.22.3.156

Dixon, J. C., Singleton, R., & Straits, B. C. (2016). *The process of social research*: Oxford University Press, USA.

Drissi, N., Ouhbi, S., Marques, G., de la Torre Díez, I., Ghogho, M., & Janati Idrissi, M. A. (2021). A systematic literature review on e-mental health solutions to assist health care workers during COVID-19. *Telemedicine and e-Health, 27*(6), 594-602. doi:https://doi.org/10.1089/tmj.2020.0287

DSM-5. (2022). *American Psychiatric Association. (2022). Diagnostic and statistical manual of mental disorders* American Psychiatric Pub.

DSM–5, t. e. (2013). *American Psychiatric Association. Diagnostic and statistical manual of mental disorders (5th ed.)*.

Dunlop, A., Lokuge, B., Masters, D., Sequeira, M., Saul, P., Dunlop, G., . . . Maher, L. (2020). Challenges in maintaining treatment services for people who use drugs during the COVID-19 pandemic. *Harm Reduction Journal, 17*(1), 26. doi:10.1186/s12954-020-00370-7

Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes*. Orlando, FL, US: Harcourt Brace Jovanovich College Publishers.

Easterby-Smith, M., Thorpe, R., & Jackson, P. R. (2012). *Management research*: Sage.

Eastwood, B., Strang, J., & Marsden, J. (2017). Effectiveness of treatment for opioid use disorder: a national, five-year, prospective, observational study in England. *Drug and alcohol dependence, 176*, 139-147.

Ebert, D. D., Zarski, A.-C., Christensen, H., Stikkelbroek, Y., Cuijpers, P., Berking, M., & Riper, H. (2015). Internet and Computer-Based Cognitive Behavioral Therapy for Anxiety and Depression in Youth: A Meta-Analysis of Randomized Controlled Outcome Trials. *PLoS ONE, 10*(3), e0119895. doi:10.1371/journal.pone.0119895

Ehrismann, M., & Stegwee, R. (2015). Trust in eHealth services. In: January). https://doi. org/10.13140/RG.

Eichenberg, C., & Wolters, C. (2012). Virtual realities in the treatment of mental disorders: A review of the current state of research. *Virtual reality in psychological, medical and pedagogical applications, 2*, 35-64.

Eid, M., Nussbeck, F. W., Geiser, C., Cole, D. A., Gollwitzer, M., & Lischetzke, T. (2008). Structural equation modeling of multitrait-multimethod data: different models for different types of methods. *Psychological Methods, 13*(3), 230.

Ek, S., Eriksson-Backa, K., & Niemelä, R. (2013). Use of and trust in health information on the Internet: A nationwide eight-year follow-up survey. *Informatics for Health and Social Care, 38*(3), 236-245.

Elahi, M. Z., Liang, G., Malik, M. J., Dilawar, S., & Ilyas, B. (2021). Fear of Covid-19 and Intentions towards Adopting E-Health Services: Exploring the Technology Acceptance Model in the Scenario of Pandemic. *International Journal of Business, Economics and Management, 8*(4), 270-291.

Elison, S., Ward, J., Davies, G., & Moody, M. (2014). Implementation of computer-assisted therapy for substance misuse: a qualitative study of Breaking Free Online using Roger's diffusion of innovation theory. *Drugs and Alcohol Today, 14*(4), 207-218.

Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of advanced nursing, 62*(1), 107-115.

Erkin, G., & Shakhrizoda, H. (2022). THE IMPORTANCE OF GEOGRAPHIC LOCATION IN TOURISM. *Uzbek Scholar Journal, 5*, 145-150.

Etgar, M. (2008). A descriptive model of the consumer co-production process. *Journal of the academy of marketing science, 36*, 97-108.

Ettner, S. L., Huang, D., Evans, E., Rose Ash, D., Hardy, M., Jourabchi, M., & Hser, Y. I. (2006). Benefit–cost in the California treatment outcome project: does substance abuse treatment “pay for itself”? *Health Services Research, 41*(1), 192-213.

Evashwick, C. (1989). Creating the continuum of care. *Health Matrix, 7*(1), 30-39.

Eyrich-Garg, K. M. (2010). Mobile Phone Technology: A New Paradigm for the Prevention, Treatment, and Research of the Non-sheltered “Street” Homeless? *Journal of Urban Health, 87*(3), 365-380. doi:10.1007/s11524-010-9456-2

Eysenbach, G. (2001). What is e-health? *J Med Internet Res, 3*(2), E20. doi:10.2196/jmir.3.2.e20

Fenichel, M., Suler, J., Barak, A., Zelvin, E., Jones, G., Munro, K., . . . Walker-Schmucker, W. (2002). Myths and realities of online clinical work. *CyberPsychology & Behavior, 5*(5), 481-497. doi://doi.org/10.1089/109493102761022904

Field, A. P. (2005). *Discovering statistics using SPSS:(and sex, drugs and rock'n'roll)*: sage.

Fishbein, M. (1979). A theory of reasoned action: Some applications and implications. *Nebraska Symposium on Motivation, 27*, 65-116.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behaviour: An introduction to theory and research*: Addison-Wesley.

Fleddermann, K., Molfenter, T., Jacobson, N., Horst, J., Roosa, M. R., Boss, D., . . . Gustafson, D. H. (2021). Clinician perspectives on barriers and facilitators to implementing e-health technology in substance use disorder (SUD) treatment facilities. *Substance Abuse: Research and Treatment, 15*, 11782218211053360.

Flückiger, C., Del Re, A. C., Wampold, B. E., & Horvath, A. O. (2018). The alliance in adult psychotherapy: A meta-analytic synthesis. *Psychotherapy, 55*(4), 316-340. doi:10.1037/pst0000172

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research, 18*(3), 382-388. doi:10.1177/002224378101800313

Fossa, A. J., Bell, S. K., & DesRoches, C. (2018). OpenNotes and shared decision making: a growing practice in clinical transparency and how it can support patient-centered care. *Journal of the American Medical Informatics Association, 25*(9), 1153-1159. doi:10.1093/jamia/ocy083

Fowler, L. A., Holt, S. L., & Joshi, D. (2016). Mobile technology-based interventions for adult users of alcohol: A systematic review of the literature. *Addictive Behaviors, 62*, 25-34. doi:https://doi.org/10.1016/j.addbeh.2016.06.008

Frampton, S. B., Charmel, P. A., & Guastello, S. (2013). *The putting patients first field guide: Global lessons in designing and implementing patient-centered care*: John Wiley & Sons.

Frazier, M. L., Johnson, P. D., & Fainshmidt, S. (2013). Development and validation of a propensity to trust scale. *Journal of Trust Research, 3*(2), 76-97. doi:10.1080/21515581.2013.820026

Gagnon, M.-P., Godin, G., Gagné, C., Fortin, J.-P., Lamothe, L., Reinharz, D., & Cloutier, A. (2003). An adaptation of the theory of interpersonal behaviour to the study of telemedicine adoption by physicians. *International journal of medical informatics, 71*(2), 103-115. doi:https://doi.org/10.1016/S1386-5056(03)00094-7

Gagnon, M.-P., Ngangue, P., Payne-Gagnon, J., & Desmartis, M. (2016). m-Health adoption by healthcare professionals: a systematic review. *Journal of the American Medical Informatics Association, 23*(1), 212-220.

Gallagher, D., Ting, L., & Palmer, A. (2008). A journey into the unknown; taking the fear out of structural equation modeling with AMOS for the first-time user. *The marketing review, 8*(3), 255-275.

Garett, R., & Young, S. D. (2023). Potential Effects of Digital Inequality on Treatment Seeking for Opioid Use Disorder. *International Journal of Mental Health and Addiction, 21*(2), 890-895. doi:10.1007/s11469-021-00629-5

Ghasemi, A., & Zahediasl, S. (2012). Normality tests for statistical analysis: a guide for non-statisticians. *International journal of endocrinology and metabolism, 10*(2), 486.

Ghauri, P., & Grønhaug, K. (2005). Research Methods in Business Studies: A Practical Guide.

Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The qualitative report, 8*(4), 597-607.

Goldstein, R. Z., & Volkow, N. D. (2011). Dysfunction of the prefrontal cortex in addiction: neuroimaging findings and clinical implications. *Nature reviews neuroscience, 12*(11), 652-669. Retrieved from https://www.nature.com/articles/nrn3119.pdf

Golinelli, D., Boetto, E., Carullo, G., Nuzzolese, A. G., Landini, M. P., & Fantini, M. P. (2020). Adoption of Digital Technologies in Health Care During the COVID-19 Pandemic: Systematic Review of Early Scientific Literature. *J Med Internet Res, 22*(11), e22280. doi:10.2196/22280

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS quarterly*, 213-236.

Gotch, C., & Hall , T. (2004). Understanding nature-related behaviors among children through a theory of reasoned action approach. *Environmental Education Research, 10*(2), 157-177. doi:10.1080/1350462042000198159

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual review of psychology, 60*, 549-576.

Gray, R. M., & Gray, R. (2009). *Probability, random processes, and ergodic properties* (Vol. 1): Springer.

Green, D. O., Creswell, J. W., Shope, R. J., & Clark, V. L. P. (2007). Grounded theory and racial/ethnic diversity. *The Sage handbook of grounded theory*, 472-492.

Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., A'Court, C., . . . Shaw, S. (2017). Beyond Adoption: A New Framework for Theorizing and Evaluating Nonadoption,

Abandonment, and Challenges to the Scale-Up, Spread, and Sustainability of Health and Care Technologies. *J Med Internet Res, 19*(11), e367. doi:10.2196/jmir.8775

Gu, D., Khan, S., Khan, I. U., Khan, S. U., Xie, Y., Li, X., & Zhang, G. (2021). Assessing the adoption of e-health technology in a developing country: an extension of the UTAUT model. *Sage Open, 11*(3), 21582440211027565. doi:DOI: 10.1177/21582440211027565

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field methods, 18*(1), 78. doi:https://doi.org/10.1177/1525822X05279

Guest, G., Namey, E. E., & Mitchell, M. L. (2013). *Collecting qualitative data: A field manual for applied research*: Sage.

Haiden A. Huskamp, A. B. B., Jeffrey Souza, Lori Uscher-Pines, Sherri Rose, Andrew Wilcock, Bruce E. Landon, and Ateev Mehrotra. (2018). How Is Telemedicine Being Used In Opioid And Other Substance Use Disorder Treatment? *Health Affairs, 37*(12), 1940-1947. doi:10.1377/hlthaff.2018.05134

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). Multivariate data analysis (Vol. 6).

Hamideh, D., & Nebeker, C. (2020). The Digital Health Landscape in Addiction and Substance Use Research: Will Digital Health Exacerbate or Mitigate Health Inequities in Vulnerable Populations? *Current Addiction Reports, 7*(3), 317-332. doi:10.1007/s40429-020-00325-9

Hardy, G., Cahill, J., & Barkham, M. (2007). Active ingredients of the therapeutic relationship that promote client change: A research perspective. *The therapeutic relationship in the cognitive behavioral psychotherapies*, 24-42.

Harrell, M. C., & Bradley, M. (2009). Data collection methods: Semi-structured interviews and focus groups.

Hartmann, H., Guthöhrlein, E. W., Siebert, M., Luehr, S., & Söding, J. (2013). P-value-based regulatory motif discovery using positional weight matrices. *Genome research, 23*(1), 181-194.

Heishman, S. J., Singleton, E. G., & Pickworth, W. B. (2008). Reliability and Validity of a Short Form of the Tobacco Craving Questionnaire. *Nicotine & Tobacco Research, 10*(4), 643-651. doi:10.1080/14622200801908174

Hennemann, S., Beutel, M. E., & Zwerenz, R. (2016). Drivers and Barriers to Acceptance of Web-Based Aftercare of Patients in Inpatient Routine Care: A Cross-Sectional Survey. *J Med Internet Res, 18*(12), e337. doi:10.2196/jmir.6003

Hermes, S., Riasanow, T., Clemons, E. K., Böhm, M., & Krcmar, H. (2020). The digital transformation of the healthcare industry: exploring the rise of emerging platform ecosystems and their influence on the role of patients. *Business Research, 13*(3), 1033-1069. doi:10.1007/s40685-020-00125-x

Hill, C. A., Dean, E., & Murphy, J. (2013). *Social media, sociality, and survey research*: John Wiley & Sons.

Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics, 43*(1), 159-172. doi:https://doi.org/10.1016/j.jbi.2009.07.002

Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International journal of medical informatics, 101*, 75-84. doi:https://doi.org/10.1016/j.ijmedinf.2017.02.002

Horvath, A. O., Del Re, A., Flückiger, C., & Symonds, D. (2011). Alliance in individual psychotherapy. *Psychotherapy, 48*(1), 9. doi: https://doi.org/10.1037/a0022186

Hossain, N., Yokota, F., Sultana, N., & Ahmed, A. (2019). Factors influencing rural end-users' acceptance of e-health in developing countries: a study on portable health clinic in

Bangladesh. *Telemedicine and e-Health, 25*(3), 221-229. Retrieved from https://doi.org/10.1089/tmj.2018.0039

Hubbard, R., & Lindsay, R. M. (2008). Why P Values Are Not a Useful Measure of Evidence in Statistical Significance Testing. *Theory & Psychology, 18*(1), 69-88. doi:10.1177/0959354307086923

Ibrahim, H., Liu, X., Zariffa, N., Morris, A. D., & Denniston, A. K. (2021). Health data poverty: an assailable barrier to equitable digital health care. *The Lancet Digital Health, 3*(4), e260-e265. doi:DOI:https://doi.org/10.1016/S2589-7500(20)30317-4

Inanlou, M., Bahmani, B., Farhoudian, A., & Rafiee, F. (2020). Addiction recovery: A systematized review. *Iranian journal of psychiatry*, 179. doi:https://doi.org/10.18502/ijps.v15i2.2691

Jacobson, N. C., Quist, R. E., Lee, C. M., & Marsch, L. A. (2023). Using digital therapeutics to target gaps and failures in traditional mental health and addiction treatments. In *Digital Therapeutics for Mental Health and Addiction* (pp. 5-18): Elsevier.

Jenn, N. C. (2006). Designing a questionnaire. *Malaysian family physician: the official journal of the Academy of Family Physicians of Malaysia, 1*(1), 32.

Johnson, R. A., & Wichern, D. W. (2007). Applied multivariate statistical analysis. 6th. *New Jersey, US: Pearson Prentice Hall*.

Jöreskog, K. G., & Goldberger, A. S. (1975). Estimation of a model with multiple indicators and multiple causes of a single latent variable. *Journal of the American statistical Association, 70*(351a), 631-639.

Kabra, G., Ramesh, A., Akhtar, P., & Dash, M. K. (2017). Understanding behavioural intention to use information technology: Insights from humanitarian practitioners. *Telematics and Informatics, 34*(7), 1250-1261. doi:https://doi.org/10.1016/j.tele.2017.05.010

Kaihlanen, A.-M., Virtanen, L., Buchert, U., Safarov, N., Valkonen, P., Hietapakka, L., . . . Heponiemi, T. (2022). Towards digital health equity-a qualitative study of the challenges experienced by vulnerable groups in using digital health services in the COVID-19 era. *BMC health services research, 22*(1), 188.

Kaminski, J. (2011). Diffusion of innovation theory. *Canadian Journal of Nursing Informatics, 6*(2), 1-6.

Kaminski, P. L. (2011). *An examination of maternal acceptance among mothers and their children with ADHD symptomatology.* Citeseer,

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons, 53*(1), 59-68. doi:https://doi.org/10.1016/j.bushor.2009.09.003

Kaplan, B., & Duchon, D. (1988). Combining Qualitative and Quantitative Methods in Information Systems Research: A Case Study. *MIS Quarterly, 12*(4), 571-586. doi:10.2307/249133

Keesara, S., Jonas, A., & Schulman, K. (2020). Covid-19 and health care's digital revolution. *New England Journal of Medicine, 382*(23), e82.

Kelpin, S. S., Parlier-Ahmad, A. B., Jallo, N., Carroll, K., & Svikis, D. S. (2022). A pilot randomized trial of CBT4CBT for women in residential treatment for substance use disorders. *Journal of Substance Abuse Treatment, 132*, 108622. doi:https://doi.org/10.1016/j.jsat.2021.108622

Khalilzadeh, J., Ozturk, A. B., & Bilgihan, A. (2017). Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry. *Computers in Human Behavior, 70*, 460-474. doi:https://doi.org/10.1016/j.chb.2017.01.001

Khan, I. U., Yu, Y., Hameed, Z., Khan, S. U., & Waheed, A. (2018). Assessing the physicians' acceptance of E-prescribing in a developing country: an extension of the UTAUT model with moderating effect of perceived organizational support. *Journal of Global Information Management (JGIM), 26*(3), 121-142.

Kim, C., & Storer, B. E. (1996). Reference values for Cook's distance. *Communications in Statistics-Simulation and Computation, 25*(3), 691-708.

Kim, S., Lee, K.-H., Hwang, H., & Yoo, S. (2016). Analysis of the factors influencing healthcare professionals' adoption of mobile electronic medical record (EMR) using the unified theory of acceptance and use of technology (UTAUT) in a tertiary hospital. *BMC Medical Informatics and Decision Making, 16*. doi:10.1186/s12911-016-0249-8

Kim, S. J., Marsch, L. A., Acosta, M. C., Guarino, H., & Aponte-Melendez, Y. (2016). Can persons with a history of multiple addiction treatment episodes benefit from technology delivered behavior therapy? A moderating role of treatment history at baseline. *Addictive Behaviors, 54*, 18-23. doi:https://doi.org/10.1016/j.addbeh.2015.11.009

King, R., Ryan, T., Senek, M., Wood, E., Taylor, B., Tod, A., . . . Robertson, S. (2022). The impact of COVID-19 on work, training and well-being experiences of nursing associates in England: a cross-sectional survey. *Nursing Open, 9*(3), 1822-1831. Retrieved from https://doi.org/10.1002/nop2.928

Kirsch, G., & Sullivan, P. A. (1992). *Methods and methodology in composition research*: SIU Press.

Kitto, S. C., Chesters, J., & Grbich, C. (2008). Quality in qualitative research. *Medical journal of Australia, 188*(4), 243-246.

Kline, R. B. (1998). Software review: Software programs for structural equation modeling: Amos, EQS, and LISREL. *Journal of psychoeducational assessment, 16*(4), 343-364.

Kline, R. B. (2005). Principles and Practice of Structural Equation Modeling, 2e éd., New York. *NY: Guilford.[Google Scholar]*.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*: Guilford publications.

Kline, T. J. (2005). *Psychological testing: A practical approach to design and evaluation*: Sage publications.

Knox, K. (2003). A Researcher's Dilemma-Philosophical and Methodological Pluralism. *Electronic journal of business research methods, 2*(2), pp145-154-pp145-154.

Kosonen, J., Shorter, G. W., & Kuusisto, K. (2024). Navigating challenges and opportunities: perspectives on digital service development in substance use disorder treatment. *Substance Abuse Treatment, Prevention, and Policy, 19*(1), 36. doi:10.1186/s13011-024-00618-6

Kowitlawakul, Y., Chan, S. W. C., Pulcini, J., & Wang, W. (2015). Factors influencing nursing students' acceptance of electronic health records for nursing education (EHRNE) software program. *Nurse education today, 35*(1), 189-194.

Kruse, C. S., Lee, K., Watson, J. B., Lobo, L. G., Stoppelmoor, A. G., & Oyibo, S. E. (2020). Measures of Effectiveness, Efficiency, and Quality of Telemedicine in the Management of Alcohol Abuse, Addiction, and Rehabilitation: Systematic Review. *J Med Internet Res, 22*(1), e13252. doi:10.2196/13252

Kshirsagar, R., Morris, R., & Bowman, S. (2017). Detecting and explaining crisis. *arXiv preprint arXiv:1705.09585*.

Kumar, A., Dangi, I., & Pawar, R. (2019). Drug addiction: A big challenge for youth and children's. *Int. J. Res. Pharm. Pharm. Sci., 4*, 35-40.

Kwak, S. K., & Kim, J. H. (2017). Statistical data preparation: management of missing values and outliers. *kja, 70*(4), 407-411. doi:10.4097/kjae.2017.70.4.407

Kyriazos, T. A. (2018). Applied psychometrics: sample size and sample power considerations in factor analysis (EFA, CFA) and SEM in general. *Psychology, 9*(08), 2207.

Lancaster, G. A., Dodd, S., & Williamson, P. R. (2004). Design and analysis of pilot studies: recommendations for good practice. *Journal of Evaluation in Clinical Practice, 10*(2), 307-312. doi:https://doi.org/10.1111/j..2002.384.doc.x

Lankton, N. K., McKnight, D. H., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the Association for Information Systems, 16*(10), 1.

Lau, F., Price, M., & Keshavjee, K. (2011). Making sense of health information system success in Canada. *Healthc Q, 14*(1), 39-46.

Lee, J., & Rho, M. J. (2013). Perception of influencing factors on acceptance of mobile health monitoring service: a comparison between users and non-users. *Healthcare informatics research, 19*(3), 167-176.

Lee, S. H. (2006). Constructing effective questionnaires. *Handbook of human performance technology, Hoboken, NJ: Pfeiffer Wiley*, 760-779.

Lee, W.-I., Fu, H.-P., Mendoza, N., & Liu, T.-Y. (2021). *Determinants impacting user behavior towards emergency use intentions of m-health services in Taiwan.* Paper presented at the Healthcare.

Leech, N. L., & Onwuegbuzie, A. J. (2008). Qualitative data analysis: A compendium of techniques and a framework for selection for school psychology research and beyond. *School Psychology Quarterly, 23*(4), 587-604. doi:10.1037/1045-3830.23.4.587

Leedy, P., & Ormrod, J. (1993). Tools of research. *LEEDY, PD Practical Research Planning and Design*.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191-204. doi:https://doi.org/10.1016/S0378-7206(01)00143-4

Leung, L. (2015). Validity, reliability, and generalizability in qualitative research. *J Family Med Prim Care, 4*(3), 324-327. doi:10.4103/2249-4863.161306

Lewis, A. (1994). Oppenheim, A. (1992). Questionnaire Design, Interviewing and Attitude Measurement, London, Pinter. Pp 303. £14.99 paperback, £39.50 hardback. ISBN 185567 0445 (pb), 185567 0437 (hb). *Journal of Community & Applied Social Psychology, 4*(5), 371-372. doi:https://doi.org/10.1002/casp.2450040506

Lewis, D., & Burke, C. J. (1949). The use and misuse of the chi-square test. *Psychological bulletin, 46*(6), 433.

Li, H., Gupta, A., Zhang, J., & Sarathy, R. (2014). Examining the decision to use standalone personal health record systems as a trust-enabled fair social contract. *Decision Support Systems, 57*, 376-386.

Lian, J.-W. (2015). Critical factors for cloud based e-invoice service adoption in Taiwan: An empirical study. *International journal of information management, 35*(1), 98-109.

Liang, Y., Wang, L., & Yuan, T.-F. (2018). Targeting Withdrawal Symptoms in Men Addicted to Methamphetamine With Transcranial Magnetic Stimulation: A Randomized Clinical Trial. *JAMA Psychiatry, 75*(11), 1199-1201. doi:10.1001/jamapsychiatry.2018.2383

Linley, J. V., Mendoza, N. S., & Resko, S. M. (2014). Working on Treatment Teams: Educating Social Work Students to Function as Addiction Specialists within Interdisciplinary Groups. *Social Work Education, 33*(5), 642-655. doi:10.1080/02615479.2014.919095

Liu, C. H., Zhang, E., Wong, G. T. F., Hyun, S., & Hahm, H. C. (2020). Factors associated with depression, anxiety, and PTSD symptomatology during the COVID-19 pandemic: Clinical implications for U.S. young adult mental health. *Psychiatry Research, 290*, 113172. doi:https://doi.org/10.1016/j.psychres.2020.113172

Liu, Y., Lu, X., Zhao, G., Li, C., & Shi, J. (2022). Adoption of mobile health services using the unified theory of acceptance and use of technology model: Self-efficacy and privacy concerns. *Front Psychol, 13*, 944976. doi:10.3389/fpsyg.2022.944976

Locke, E. A. (2012). Construct validity vs. concept validity. *Human Resource Management Review, 22*(2), 146-148.

López-Pelayo, H., Aubin, H.-J., Drummond, C., Dom, G., Pascual, F., Rehm, J., . . . Gual, A. (2020). "The post-COVID era": challenges in the treatment of substance use disorder (SUD) after the pandemic. *BMC Medicine, 18*(1), 241. doi:10.1186/s12916-020-01693-9

Lowenstein, M., Perrone, J., Xiong, R. A., Snider, C. K., O'Donnell, N., Hermann, D., . . . Khatri, U. (2022). Sustained implementation of a multicomponent strategy to increase emergency department-initiated interventions for opioid use disorder. *Annals of Emergency Medicine, 79*(3), 237-248.

Ma, Q., Chan, A. H. S., & Chen, K. (2016). Personal and other factors affecting acceptance of smartphone technology by older Chinese adults. *Applied Ergonomics, 54*, 62-71. doi:https://doi.org/10.1016/j.apergo.2015.11.015

Mahmood, A., Kedia, S., Wyant, D. K., Ahn, S., & Bhuyan, S. S. (2019). Use of mobile health applications for health-promoting behavior among individuals with chronic medical conditions. *DIGITAL HEALTH, 5*, 2055207619882181. doi:10.1177/2055207619882181

Mallen, M. J., Day, S. X., & Green, M. A. (2003). Online versus face-to-face conversation: An examination of relational and discourse variables. *Psychotherapy: Theory, research, practice, training, 40*(1-2), 155. Retrieved from https://doi.org/10.1037/0033-3204.40.1-2.155

Mamun, M. A., & Griffiths, M. D. (2020). First COVID-19 suicide case in Bangladesh due to fear of COVID-19 and xenophobia: Possible suicide prevention strategies. *Asian J Psychiatr, 51*, 102073. doi:10.1016/j.ajp.2020.102073

Manning, M., Smith, C., & Mazerolle, P. (2013). The societal costs of alcohol misuse in Australia. *Trends and Issues in Crime and Criminal Justice [electronic resource]*(454), 1-6. Retrieved from https://search.informit.org/doi/10.3316/informit.252274353879646

https://search.informit.org/doi/full/10.3316/informit.252274353879646

Manuel, J. I., Yuan, Y., Herman, D. B., Svikis, D. S., Nichols, O., Palmer, E., & Deren, S. (2017). Barriers and facilitators to successful transition from long-term residential substance abuse treatment. *Journal of Substance Abuse Treatment, 74*, 16-22. doi:https://doi.org/10.1016/j.jsat.2016.12.001

Marcu, G., Ondersma, S. J., Spiller, A. N., Broderick, B. M., Kadri, R., & Buis, L. R. (2022). The Perceived Benefits of Digital Interventions for Behavioral Health: Qualitative Interview Study. *J Med Internet Res, 24*(3), e34300. doi:10.2196/34300

Marikyan, D., & Papagiannidis, S. (2023). Task-technology fit: a review. *TheoryHub Book*.

Marsch, L. A., Campbell, A., Campbell, C., Chen, C.-H., Ertin, E., Ghitza, U., . . . Young, S. (2020). The application of digital health to the assessment and treatment of substance use disorders: The past, current, and future role of the National Drug Abuse Treatment Clinical Trials Network. *Journal of Substance Abuse Treatment, 112*, 4-11. doi:https://doi.org/10.1016/j.jsat.2020.02.005

Marshall, B., Mills, R., & Olsen, D. (2008). The role of end-user training in technology acceptance. *Review of Business Information Systems (RBIS), 12*(2), 1-8.

Martin, D. J., Garske, J. P., & Davis, M. K. (2000). Relation of the therapeutic alliance with outcome and other variables: A meta-analytic review. *Journal of Consulting and Clinical Psychology, 68*(3), 438-450. doi:10.1037/0022-006X.68.3.438

Martin, S., Kelly, G., Kernohan, W. G., McCreight, B., & Nugent, C. (2008). Smart home technologies for health and social care support. *Cochrane Database of Systematic Reviews*(4). doi:10.1002/14651858.CD006412.pub2

Marwaha, J. S., Landman, A. B., Brat, G. A., Dunn, T., & Gordon, W. J. (2022). Deploying digital health tools within large, complex health systems: key considerations for adoption and implementation. *npj Digital Medicine, 5*(1), 13. doi:10.1038/s41746-022-00557-1

Matheson, J. L. (2007). The Voice Transcription Technique: Use of Voice Recognition Software to Transcribe Digital Interview Data in Qualitative Research. *Qualitative Report, 12*(4), 547-560.

McDonnell, A., MacNeill, C., Chapman, B., Gilbertson, N., Reinhardt, M., & Carreiro, S. (2021). Leveraging digital tools to support recovery from substance use disorder during the COVID-19 pandemic response. *Journal of Substance Abuse Treatment, 124*, 108226. doi:https://doi.org/10.1016/j.jsat.2020.108226

McEachan, R. R. C., Conner, M., Taylor, N. J., & Lawton, R. J. (2011). Prospective prediction of health-related behaviours with the Theory of Planned Behaviour: a meta-analysis. *Health Psychology Review, 5*(2), 97-144. doi:10.1080/17437199.2010.521684

McGrail, M. R., Humphreys, J. S., Joyce, C., Scott, A., & Kalb, G. (2011). Rural amenity and medical workforce shortage: is there a relationship? *Geographical Research, 49*(2), 192-202.

McGrail, M. R., Wingrove, P. M., Petterson, S. M., Humphreys, J. S., Russell, D. J., & Bazemore, A. W. (2017). Measuring the attractiveness of rural communities in accounting for differences of rural primary care workforce supply. *Rural and remote health, 17*(2), 1-12. Retrieved from https://search.informit.org/doi/10.3316/informit.149604144858540

https://search.informit.org/doi/full/10.3316/informit.149604144858540

McKay, J. R., Franklin, T. R., Patapis, N., & Lynch, K. G. (2006). Conceptual, methodological, and analytical issues in the study of relapse. *Clinical Psychology Review, 26*(2), 109-127. doi:https://doi.org/10.1016/j.cpr.2005.11.002

McLellan, A. T., & Woodworth, A. M. (2014). The affordable care act and treatment for "substance use disorders:" implications of ending segregated behavioral healthcare. *Journal of Substance Abuse Treatment, 46*(5), 541-545.

Meade, A. W., Johnson, E. C., & Braddy, P. W. (2008). Power and sensitivity of alternative fit indices in tests of measurement invariance. *Journal of applied psychology, 93*(3), 568.

Menon, J., & Kandasamy, A. (2018). Relapse prevention. *Indian Journal of Psychiatry, 60*(Suppl 4), S473.

Menon, R., Meyer, J., Nippak, P., & Begum, H. (2022). Smartphone Alcohol Use Disorder Recovery Apps: Cross-sectional Survey of Behavioral Intention to Use. *JMIR Hum Factors, 9*(2), e33493. doi:10.2196/33493

Mensah, I. K., Zeng, G., & Mwakapesa, D. S. (2022). The behavioral intention to adopt mobile health services: The moderating impact of mobile self-efficacy. *Front Public Health, 10*, 1020474. doi:10.3389/fpubh.2022.1020474

Merritt, S. M., Heimbaugh, H., LaChapell, J., & Lee, D. (2013). I trust it, but I don't know why: Effects of implicit attitudes toward automation on trust in an automated system. *Human factors, 55*(3), 520-534.

Merz, F. (2018). United Nations Office on Drugs and Crime: World Drug Report 2017. 2017. *SIRIUS-Zeitschrift für Strategische Analysen, 2*(1), 85-86.

Meskó, B., Drobni, Z., Bényei, É., Gergely, B., & Győrffy, Z. (2017). Digital health is a cultural transformation of traditional healthcare. *Mhealth, 3*, 38. doi:10.21037/mhealth.2017.08.07

Meskó, B., Radó, N., & Győrffy, Z. (2019). Opinion leader empowered patients about the era of digital health: a qualitative study. *BMJ Open, 9*(3), e025267.

Michelle M. Ng, B.A. ,, Joseph Firth, Ph.D. ,, Mia Minen, M.D. ,, & John Torous, M.D. (2019). User Engagement in Mental Health Apps: A Review of Measurement, Reporting, and Validity. *Psychiatric Services, 70*(7), 538-544. doi:10.1176/appi.ps.201800519

Middendorp, C. P. (1991). On the conceptualization of theoretical constructs. *Quality and Quantity, 25*(3), 235-252.

Miller, W. R., & Moyers, T. B. (2015). The forest and the trees: relational and specific factors in addiction treatment. *Addiction, 110*(3), 401-413. doi:10.1111/add.12693

Mitchell, J. (1999). *From telehealth to e-health: the unstoppable rise of e-health*: Department of Communications, Information Technology and the Arts.

Mohajan, H. K. (2017). Two criteria for good measurements in research: Validity and reliability. *Annals of Spiru Haret University. Economic Series, 17*(4), 59-82.

Mohamad, M. M., Sulaiman, N. L., Sern, L. C., & Salleh, K. M. (2015). Measuring the Validity and Reliability of Research Instruments. *Procedia - Social and Behavioral Sciences, 204*, 164-171. doi:https://doi.org/10.1016/j.sbspro.2015.08.129

Moore, D., & McCabe, G. (2006). Producing data. *Introduction to the Practice of Statistics*, 191-250.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research, 2*(3), 192-222.

Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological bulletin, 105*(3), 430.

Nachtigall, C., Kroehne, U., Funke, F., & Steyer, R. (2003). Pros and cons of structural equation modeling. *Methods Psychological Research Online, 8*(2), 1-22.

Najavits, L. M., Crits-Christoph, P., & Dierberger, A. (2000). Clinicians' Impact on the Quality of Substance Use Disorder Treatment. *Substance Use & Misuse, 35*(12-14), 2161-2190. doi:10.3109/10826080009148253

Nickel, P. J., Franssen, M., & Kroes, P. (2010). Can We Make Sense of the Notion of Trustworthy Technology? *Knowledge, Technology & Policy, 23*(3), 429-444. doi:10.1007/s12130-010-9124-6

Norcross, J. C., & Lambert, M. J. (2018). Psychotherapy relationships that work III. *Psychotherapy, 55*(4), 303.

Norman, C. D., & Skinner, H. A. (2006a). eHEALS: the eHealth literacy scale. *Journal of medical Internet research, 8*(4), e507.

Norman, C. D., & Skinner, H. A. (2006b). eHealth literacy: essential skills for consumer health in a networked world. *Journal of Medical Internet Research, 8*(2), e506.

O'Dowd, A. (2020). Drug misuse rose 30% in past decade and covid-19 could worsen situation, UN report warns. *BMJ: British Medical Journal (Online), 369*.

Olken, F., & Rotem, D. (1986). Simple random sampling from relational databases.

Onwuegbuzie, A. J., Collins, K. M. T., & Frels, R. K. (2013). Foreword. *International Journal of Multiple Research Approaches, 7*(1), 2-8. doi:10.5172/mra.2013.7.1.2

Osubor, V., & Chiemeke, S. (2015). The impacts of information culture on e-learning innovation adoption in learning institutions in Nigeria. *African Journal of Computing and ICT, 8*(1), 17-26.

Pampaka, M., Hutcheson, G., & Williams, J. (2016). Handling missing data: analysis of a challenging data set using multiple imputation. *International Journal of Research & Method in Education, 39*(1), 19-37.

Panch, T., Szolovits, P., & Atun, R. (2018). Artificial intelligence, machine learning and health systems. *J Glob Health, 8*(2), 020303. doi:10.7189/jogh.08.020303

Patel, V., Saxena, S., Lund, C., Thornicroft, G., Baingana, F., Bolton, P., . . . UnÜtzer, J. (2018). The Lancet Commission on global mental health and sustainable development. *The Lancet, 392*(10157), 1553-1598. doi:https://doi.org/10.1016/S0140-6736(18)31612-X

Patrick, K., Hekler, E. B., Estrin, D., Mohr, D. C., Riper, H., Crane, D., . . . Riley, W. T. (2016). The Pace of Technologic Change: Implications for Digital Health Behavior Intervention Research.

American Journal of Preventive Medicine, 51(5), 816-824. doi:https://doi.org/10.1016/j.amepre.2016.05.001

Patton, M. Q. (2014). *Qualitative research & evaluation methods: Integrating theory and practice*: Sage publications.

Paunov, C., & Planes-Satorra, S. (2021). What future for science, technology and innovation after COVID-19? doi:doi:https://doi.org/10.1787/de9eb127-en

Perle, J. G., Langsam, L. C., Randel, A., Lutchman, S., Levine, A. B., Odland, A. P., . . . Marker, C. D. (2013). Attitudes Toward Psychological Telehealth: Current and Future Clinical Psychologists' Opinions of Internet-Based Interventions. *Journal of Clinical Psychology, 69*(1), 100-113. doi:https://doi.org/10.1002/jclp.21912

Perski, O., Baretta, D., Blandford, A., West, R., & Michie, S. (2018). Engagement features judged by excessive drinkers as most important to include in smartphone applications for alcohol reduction: A mixed-methods study. *Digital health, 4*, 2055207618785841.

Pierce, B. S., Perrin, P. B., Tyler, C. M., McKee, G. B., & Watson, J. D. (2021). The COVID-19 telepsychology revolution: A national study of pandemic-based changes in U.S. mental health care delivery. *Am Psychol, 76*(1), 14-25. doi:10.1037/amp0000722

Plas, J. M., Kvale, S., & KVALE, S. A. (1996). Interviews: An introduction to qualitative research interviewing. In: Sage.

Ponto, J. (2015). Understanding and Evaluating Survey Research. *J Adv Pract Oncol, 6*(2), 168-171.

Porfilio-Mathieu, L., Pigeon-Gagné, É., Dagenais, C., & Ridde, V. (2022). Prevalence and determinants of mental health among an indigent population in rural Burkina Faso: a cross-sectional study. *Journal of Global Health Reports, 6*, e2022017. doi:doi:10.29392/001c.33820

Porter, C. E., & Donthu, N. (2006). Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics. *Journal of Business Research, 59*(9), 999-1007.

Poston, J. M., & Hanson, W. E. (2010). Meta-analysis of psychological assessment as a therapeutic intervention. *Psychological assessment, 22*(2), 203.

Pouletty, P. (2002). Drug addictions: towards socially accepted and medically treatable diseases. *Nature Reviews Drug Discovery, 1*(9), 731-736.

Preacher, K. J., & Yaremych, H. E. (2023). Model selection in structural equation modeling. *Handbook of structural equation modeling*, 206-222.

Putteeraj, M., Bhungee, N., Somanah, J., & Moty, N. (2022). Assessing E-Health adoption readiness using diffusion of innovation theory and the role mediated by each adopter's category in a Mauritian context. *International Health, 14*(3), 236-249.

Rahimi, B., Nadri, H., Afshar, H. L., & Timpka, T. (2018). A systematic review of the technology acceptance model in health informatics. *Applied clinical informatics, 9*(03), 604-634.

Ramsetty, A., & Adams, C. (2020). Impact of the digital divide in the age of COVID-19. *J Am Med Inform Assoc, 27*(7), 1147-1148. doi:10.1093/jamia/ocaa078

Ramsey, Z. S., Davidov, D. M., Levy, C. B., & Abildso, C. G. (2022). An etic view of LGBTQ healthcare: Barriers to access according to healthcare providers and researchers. *Journal of Gay & Lesbian Social Services, 34*(4), 502-520. doi:10.1080/10538720.2022.2042452

Reeves, J. J., Hollandsworth, H. M., Torriani, F. J., Taplitz, R., Abeles, S., Tai-Seale, M., . . . Longhurst, C. A. (2020). Rapid response to COVID-19: health informatics support for outbreak management in an academic health system. *Journal of the American Medical Informatics Association, 27*(6), 853-859. doi:10.1093/jamia/ocaa037

Rehm, J., Marmet, S., Anderson, P., Gual, A., Kraus, L., Nutt, D. J., . . . Gmel, G. (2013). Defining Substance Use Disorders: Do We Really Need More Than Heavy Use? *Alcohol and Alcoholism, 48*(6), 633-640. doi:10.1093/alcalc/agt127

Rejali, S., Aghabayk, K., Esmaeli, S., & Shiwakoti, N. (2023). Comparison of technology acceptance model, theory of planned behavior, and unified theory of acceptance and use of technology to assess a priori acceptance of fully automated vehicles. *Transportation Research Part A: Policy and Practice, 168*, 103565. doi:https://doi.org/10.1016/j.tra.2022.103565

Richards, P., & Simpson, S. (2015). Beyond the therapeutic hour: an exploratory pilot study of using technology to enhance alliance and engagement within face-to-face psychotherapy. *British Journal of Guidance & Counselling, 43*(1), 57-93. doi:10.1080/03069885.2014.936824

Richards, P., Simpson, S., Bastiampillai, T., Pietrabissa, G., & Castelnuovo, G. (2018). The impact of technology on therapeutic alliance and engagement in psychotherapy: The therapist's perspective. *Clinical Psychologist, 22*(2), 171-181. doi:10.1111/cp.12102

Riper, H., & Tait, R. (2013). Using the Internet for alcohol and drug prevention. In *Interventions for addiction: Comprehensive addictive behaviors and disorders* (pp. 855-863): Elsevier.

Ritchie, H., & Roser, M. (2019). Drug use. *Our world in data*.

Robotham, D., Satkunanathan, S., Doughty, L., & Wykes, T. (2016). Do We Still Have a Digital Divide in Mental Health? A Five-Year Survey Follow-up. *J Med Internet Res, 18*(11), e309. doi:10.2196/jmir.6511

Rogers, C. R. (1995). *A way of being*: Houghton Mifflin Harcourt.

Rogers, E. M. (1962). *Diffusion of innovations*: Simon and Schuster.

Rogers, E. M. (1983). *DIFFUSION OF INNOVATIONS 3RD E REV*: New York: Free Press; London: Collier Macmillan.

Rogers, E. M. (2010). *Diffusion of innovations*: Simon and Schuster.

Rosa, C., Campbell, A. N. C., Miele, G. M., Brunner, M., & Winstanley, E. L. (2015). Using e-technologies in clinical trials. *Contemporary Clinical Trials, 45*, 41-54. doi:https://doi.org/10.1016/j.cct.2015.07.007

Ryan, T. J., Alarcon, G. M., Walter, C., Gamble, R., Jessup, S. A., Capiola, A., & Pfahler, M. D. (2019, 2019//). *Trust in Automated Software Repair.* Paper presented at the HCI for Cybersecurity, Privacy and Trust, Cham.

Sadoughi, F., Khodaveisi, T., & Ahmadi, H. (2019). The used theories for the adoption of electronic health record: a systematic literature review. *Health and Technology, 9*(4), 383-400. doi:10.1007/s12553-018-0277-8

SAMHSA. (2016). Substance, Abuse Mental Health Services, Administration. The Surgeon General's Report on Alcohol, Drugs, and Health. In *Facing Addiction in America: The Surgeon General's Report on Alcohol, Drugs, and Health*. Washington (DC): US Department of Health and Human Services.

Sanders, E. B. N., & Stappers, P. J. (2008). Co-creation and the new landscapes of design. *CoDesign, 4*(1), 5-18. doi:10.1080/15710880701875068

Sankaranarayanan, J., & Sallach, R. E. (2014). Rural patients' access to mobile phones and willingness to receive mobile phone-based pharmacy and other health technology services: a pilot study. *Telemedicine and e-Health, 20*(2), 182-185.

Sarmiento, C., & Lau, C. (2020). Diagnostic and statistical manual of mental disorders: DSM-5. *The Wiley Encyclopedia of Personality and Individual Differences: Personality Processes and Individual Differences*, 125-129.

Scharfstein, D. O., Hogan, J., & Herman, A. (2012). Randomized trials in orthopaedic surgery: advances and future directions: on the prevention and analysis of missing data in

randomized clinical trials: the state of the art. *The Journal of Bone and Joint surgery. American Volume, 94*(Suppl 1), 80.

Schueller, S. M., Washburn, J. J., & Price, M. (2016). Exploring mental health providers' interest in using web and mobile-based tools in their practices. *Internet Interventions, 4*, 145-151. doi:https://doi.org/10.1016/j.invent.2016.06.004

Schulte, M., Liang, D., Wu, F., Lan, Y.-C., Tsay, W., Du, J., . . . Hser, Y. I. (2016). A Smartphone Application Supporting Recovery from Heroin Addiction: Perspectives of Patients and Providers in China, Taiwan, and the USA. *Journal of Neuroimmune Pharmacology, 11*(3), 511-522. doi:10.1007/s11481-016-9653-1

Sekaran, U., & Bougie, R. (2003). Research Methods For Business, A Skill Building Approach, John Willey & Sons. *Inc. New York, 29*.

Shahab, L., & McEwen, A. (2009). Online support for smoking cessation: a systematic review of the literature. *Addiction, 104*(11), 1792-1804. doi:https://doi.org/10.1111/j.1360-0443.2009.02710.x

Siebert, J. N., Gosetto, L., Sauvage, M., Bloudeau, L., Suppan, L., Rodieux, F., . . . Lovis, C. (2022). Usability Testing and Technology Acceptance of an mHealth App at the Point of Care During Simulated Pediatric In-and Out-of-Hospital Cardiopulmonary Resuscitations: Study Nested Within 2 Multicenter Randomized Controlled Trials. *JMIR human factors, 9*(1), e35399.

Simon, B. (2001). Wissensmedien im Bildungssektor. Eine Akzeptanzuntersuchung an Hochschulen. 179.

Singer, J. B., & Sage, M. (2015). Technology and social work practice: Micro, mezzo, and macro applications.

Singleton Jr, R., Straits, B. C., Straits, M. M., & McAllister, R. J. (1988). *Approaches to social research*: Oxford University Press.

Singleton, R., Straits, B., Straits, M., & McAlister, R. (1999). Approaches to Social Research: Oxford University Press. *New York and Oxford, 9*.

Six, F., de Vadder, S., Glavina, M., Verhoest, K., & Pepermans, K. (2023). What drives compliance with COVID-19 measures over time? Explaining changing impacts with Goal Framing Theory. *Regulation & Governance, 17*(1), 3-21. doi:https://doi.org/10.1111/rego.12440

Skinner, N., McEntee, A., & Roche, A. (2020a). AOD worker health and wellbeing: Australia's Alcohol and Other Drug (AOD) Workforce Survey 2019–2020.

Skinner, N., McEntee, A., & Roche, A. (2020b). Australia's alcohol and other drug workforce: National survey results 2019-2020. *Adelaide, South Australia: National Centre for Education and Training on Addiction (NCETA), Flinders University*.

Slade, E. L., Williams, M., & Dwivedi, Y. (2013). An extension of the UTAUT 2 in a healthcare context.

Smith, B., & Magnani, J. W. (2019). New technologies, new disparities: The intersection of electronic health and digital health literacy. *International Journal of Cardiology, 292*, 280-282. doi:https://doi.org/10.1016/j.ijcard.2019.05.066

Smith, H. J., Milberg, S. J., & Burke, S. J. (1996). Information Privacy: Measuring Individuals' Concerns about Organizational Practices. *MIS Quarterly, 20*(2), 167-196. doi:10.2307/249477

Smith, H. J., Milberg, S. J., & Burke, S. J. (1996). Information privacy: Measuring individuals' concerns about organizational practices. *MIS quarterly*, 167-196.

Smith, T. D., & McMillan, B. F. (2001). A Primer of Model Fit Indices in Structural Equation Modeling.

Sniehotta, F. F., Presseau, J., & Araújo-Soares, V. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review, 8*(1), 1-7. doi:10.1080/17437199.2013.869710

Soni, S., Sharma, A., Khinchi, M., Gauttam, N., & Gauttam, S. (2017). A Review On: Substance Abuse. *Asian Journal of Pharmaceutical Research and Development*, 1-7.

Sood, S., Mbarika, V., Jugoo, S., Dookhy, R., Doarn, C. R., Prakash, N., & Merrell, R. C. (2007). What is telemedicine? A collection of 104 peer-reviewed perspectives and theoretical underpinnings. *Telemedicine and e-Health, 13*(5), 573-590. doi:https://doi.org/10.1089/tmj.2006.0073

Srivastava, K., Chaudhury, S., Dhamija, S., Prakash, J., & Chatterjee, K. (2020). Digital technological interventions in mental health care. *Ind Psychiatry J, 29*(2), 181-184. doi:10.4103/ipj.ipj_32_21

Stiles-Shields, C., Kwasny, M. J., Cai, X., & Mohr, D. C. (2014). Therapeutic alliance in face-to-face and telephone-administered cognitive behavioral therapy. *Journal of Consulting and Clinical Psychology, 82*(2), 349-354. doi:10.1037/a0035554

Streiner, D. L. (2006). Building a better model: an introduction to structural equation modelling. *The Canadian Journal of Psychiatry, 51*(5), 317-324.

Šumak, B., Pušnik, M., Heričko, M., & Šorgo, A. (2017). Differences between prospective, existing, and former users of interactive whiteboards on external factors affecting their adoption, usage and abandonment. *Computers in Human Behavior, 72*, 733-756. doi:https://doi.org/10.1016/j.chb.2016.09.006

Sun, Y., Wang, N., Guo, X., & Peng, Z. (2013). Understanding the acceptance of mobile health services: a comparison and integration of alternative models. *Journal of electronic commerce research, 14*(2), 183.

Tabachnick, B. G., & Fidell, L. S. (2007). *Experimental designs using ANOVA* (Vol. 724): Thomson/Brooks/Cole Belmont, CA.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing, 22*, 960-967. doi:https://doi.org/10.1016/j.promfg.2018.03.137

Tangcharoensathien, V., Witthayapipopsakul, W., Panichkriangkrai, W., Patcharanarumol, W., & Mills, A. (2018). Health systems development in Thailand: a solid platform for successful implementation of universal health coverage. *The Lancet, 391*(10126), 1205-1223. doi:https://doi.org/10.1016/S0140-6736(18)30198-3

Tashakkori, A., & Creswell, J. W. (2007). Exploring the nature of research questions in mixed methods research. In (Vol. 1, pp. 207-211): Sage Publications Sage CA: Los Angeles, CA.

Tashakkori, A., & Teddlie, C. (2008). Quality of inferences in mixed methods research: Calling for an integrative framework. *Advances in mixed methods research, 53*(7), 101-119.

Tavousi, M., Montazeri, A., Hidarnia, A., Hajizadeh, E., Taremian, F., & Haerimehrizi, A. (2015). Substance use avoidance among Iranian male adolescents: a comparison of three versions of the theory of reasoned action. *International Journal of Adolescent Medicine and Health, 27*(3), 329-334. doi:doi:10.1515/ijamh-2014-0034

Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International Journal of Research in Marketing, 12*(2), 137-155. doi:https://doi.org/10.1016/0167-8116(94)00019-K

Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research, 6*(2), 144-176. doi:10.1287/isre.6.2.144

Teo, T. S., & Men, B. (2008). Knowledge portals in Chinese consulting firms: a task–technology fit perspective. *European Journal of Information Systems, 17*(6), 557-574.

Thakkar, J. J., & Thakkar, J. J. (2020). Applications of structural equation modelling with AMOS 21, IBM SPSS. *Structural Equation Modelling: Application for Research and Practice (with AMOS and R)*, 35-89.

Thilakarathne, N. N., Kagita, M. K., & Gadekallu, T. R. (2020). The role of the internet of things in health care: a systematic and comprehensive study. *Available at SSRN 3690815*. doi:https://doi.org/10.31033/ijemr.10.4.22

Thorne, S. (2000). Data analysis in qualitative research. *Evidence Based Nursing, 3*(3), 68-70. doi:10.1136/ebn.3.3.68

Ticehurst, G. W., & Veal, A. J. (2000). *Business Research Methods: A Managerial Approach*: Longman.

Tofighi, B., Nicholson, J. M., McNeely, J., Muench, F., & Lee, J. D. (2017). Mobile phone messaging for illicit drug and alcohol dependence: A systematic review of the literature. *Drug and Alcohol Review, 36*(4), 477-491. doi:https://doi.org/10.1111/dar.12535

Tojib, D., & Tsarenko, Y. (2012). Post-adoption modeling of advanced mobile service use. *Journal of Business Research, 65*(7), 922-928.

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*: Lexington books.

Tung, F.-C., Chang, S.-C., & Chou, C.-M. (2008). An extension of trust and TAM model with IDT in the adoption of the electronic logistics information system in HIS in the medical industry. *International Journal of Medical Informatics, 77*(5), 324-335. doi:https://doi.org/10.1016/j.ijmedinf.2007.06.006

Turner, L. (2005). SOCIAL WORK PRACTICE IN CANADA'S OFFICIALLY BILINGUAL PROVINCE: Challenges and Opportunities. *Canadian Social Work Review / Revue canadienne de service social, 22*(2), 131-154. Retrieved from http://www.jstor.org/stable/41669832

Turner, M., Kitchenham, B., Brereton, P., Charters, S., & Budgen, D. (2010). Does the technology acceptance model predict actual use? A systematic literature review. *Information and Software Technology, 52*(5), 463-479. doi:https://doi.org/10.1016/j.infsof.2009.11.005

Turocy, P. S. (2002). Survey research in athletic training: the scientific method of development and implementation. *Journal of Athletic Training, 37*(4 suppl), S-174.

Uscher-Pines, L., Cantor, J., Huskamp, H. A., Mehrotra, A., Busch, A., & Barnett, M. (2020). Adoption of telemedicine services by substance abuse treatment facilities in the U.S. *Journal of Substance Abuse Treatment, 117*, 108060. doi:https://doi.org/10.1016/j.jsat.2020.108060

Vargo, D., Zhu, L., Benwell, B., & Yan, Z. (2021). Digital technology use during COVID-19 pandemic: A rapid review. *Human Behavior and Emerging Technologies, 3*(1), 13-24. doi:https://doi.org/10.1002/hbe2.242

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 46*(2), 186-204. doi:10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: US vs. China. *Venkatesh, V. and Zhang, X."Unified Theory of Acceptance and Use of Technology: US Vs. China," Journal of Global Information Technology Management (13: 1)*, 5-27. Retrieved from https://ssrn.com/abstract=4061406

Vidrine, D. J., Frank-Pearce, S. G., Vidrine, J. I., Tahay, P. D., Marani, S. K., Chen, S., . . . Prokhorov, A. V. (2019). Efficacy of Mobile Phone–Delivered Smoking Cessation Interventions for Socioeconomically Disadvantaged Individuals: A Randomized Clinical Trial. *JAMA Internal Medicine, 179*(2), 167-174. doi:10.1001/jamainternmed.2018.5713

Voce, A., & Sullivan, T. (2022). What are the monetary returns of investing in programs that reduce demand for illicit drugs? *Trends and Issues in Crime and Criminal Justice [electronic resource]*(657), 1-28. doi:doi/10.3316/agispt.20220926074744

Voogt, C. V., Poelen, E. A. P., Kleinjan, M., Lemmers, L. A. C. J., & Engels, R. C. M. E. (2013). The Effectiveness of the 'What Do You Drink' Web-based Brief Alcohol Intervention in Reducing Heavy Drinking among Students: A Two-arm Parallel Group Randomized Controlled Trial. *Alcohol and Alcoholism, 48*(3), 312-321. doi:10.1093/alcalc/ags133

Walsh, L., Hemsley, B., Allan, M., Adams, N., Balandin, S., Georgiou, A., . . . Hill, S. (2017). The e-health literacy demands of Australia's my health record: a heuristic evaluation of usability. *Perspectives in health information management, 14*(Fall).

Wang, L., Wang, Q., Davis, P. B., Volkow, N. D., & Xu, R. (2022). Increased risk for COVID-19 breakthrough infection in fully vaccinated patients with substance use disorders in the United States between December 2020 and August 2021. *World Psychiatry, 21*(1), 124-132.

Wang, Y. D., & Emurian, H. H. (2005). An overview of online trust: Concepts, elements, and implications. *Computers in Human Behavior, 21*(1), 105-125. doi:https://doi.org/10.1016/j.chb.2003.11.008

Welch, V., Petkovic, J., Pardo Pardo, J., Rader, T., & Tugwell, P. (2016). Interactive social media interventions to promote health equity: an overview of reviews. *Health Promot Chronic Dis Prev Can, 36*(4), 63-75. doi:10.24095/hpcdp.36.4.01

Welle-Strand, G. K., Gjersing, L., Olsen, I. K., & Clausen, T. (2022). A COVID-19 Survey among People Who Use Drugs in Norway. *International Journal of Environmental Research and Public Health, 19*(12), 7002.

Wells, E. A., Kristman-Valente, A. N., Peavy, K. M., & Jackson, T. R. (2013). Social Workers and Delivery of Evidence-Based Psychosocial Treatments for Substance Use Disorders. *Social Work in Public Health, 28*(3-4), 279-301. doi:10.1080/19371918.2013.759033

Whetton, S., Shanahan, M., Cartwright, K., Duraisingam, V., Ferrante, A., Gray, D., . . . Pidd, K. (2016). The social costs of methamphetamine in Australia 2013/14. doi:http://hdl.handle.net/20.500.11937/55464

Whetton, S., Tait, R., Chrzanowska, A., Donnelly, N., McEntee, A., Mukhtar, A., . . . Dey, T. (2020). Quantifying the Social Costs of Cannabis Use to Australia in 2015/16 (https://ndri. curtin. edu. au/ndri/media/documents/publications. *T287. pdf*.

Whetton, S., Tait, R., Gilmore, W., Dey, T., Agramunt, S., Halim, S. A., . . . Allsop, S. (2021). Examining the social and economic costs of alcohol use in Australia: 2017/18.

WHO. (2021). Global strategy on digital health 2020-2025. Retrieved from https://www.who.int/docs/default-source/documents/gs4dhdaa2a9f352b0445bafbc79ca799dce4d.pdf

WHO. (2023). eHealth. Retrieved from https://www.emro.who.int/health-topics/ehealth/

Wilson, N. W., Couper, I. D., De Vries, E., Reid, S., Fish, T., & Marais, B. J. (2009). A critical review of interventions to redress the inequitable distribution of healthcare professionals to rural and remote areas. *Rural and remote health, 9*(2), 1-21. Retrieved from https://search.informit.org/doi/10.3316/informit.496326474031125

https://search.informit.org/doi/full/10.3316/informit.496326474031125

Wood, F. (2006). *Keywords in Qualitative Methods : A Vocabulary of Research Concepts*. Retrieved from http://digital.casalini.it/9781847877550

http://digital.casalini.it/4912785

Woods, D., & Dekker, S. (2000). Anticipating the effects of technological change: A new era of dynamics for human factors. *Theoretical Issues in Ergonomics Science, 1*(3), 272-282. doi:10.1080/14639220110037452

Zaabar, B., Cheikhrouhou, O., Jamil, F., Ammi, M., & Abid, M. (2021). HealthBlock: A secure blockchain-based healthcare data management system. *Computer Networks, 200*, 108500. doi:https://doi.org/10.1016/j.comnet.2021.108500

Zewdu, S., Hanlon, C., Fekadu, A., Medhin, G., & Teferra, S. (2019). Treatment gap, help-seeking, stigma and magnitude of alcohol use disorder in rural Ethiopia. *Substance abuse treatment, prevention, and policy, 14*(1), 1-10.

Zhang, X., Han, X., Dang, Y., Meng, F., Guo, X., & Lin, J. (2017). User acceptance of mobile health services from users' perspectives: The role of self-efficacy and response-efficacy in technology acceptance. *Informatics for Health and Social Care, 42*(2), 194-206. doi:10.1080/17538157.2016.1200053

Zhang, X., Yan, X., Cao, X., Sun, Y., Chen, H., & She, J. (2018). The role of perceived e-health literacy in users' continuance intention to use mobile healthcare applications: an exploratory empirical study in China. *Information Technology for Development, 24*(2), 198-223. doi:10.1080/02681102.2017.1283286

Zhao, Y., Lei, J., & Conway, P. F. (2006). Global Perspective on Political Definitions of E-learning: Commonalities and Differences in National Educational Technology Strategy Discourses. In J. Weiss, J. Nolan, J. Hunsinger, & P. Trifonas (Eds.), *The International Handbook of Virtual Learning Environments* (pp. 673-697). Dordrecht: Springer Netherlands.

Zhu, K., & Kraemer, K. L. (2005). Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry. *Information Systems Research, 16*(1), 61-84. doi:10.1287/isre.1050.0045