RESULTS FROM TWO DISCRETE CHOICE CONJOINT EXPERIMENTS

EXAMINING PATIENT-PREFERRED ATTRIBUTES TO ENCOURAGE MENTAL

HEALTH TREATMENT INITIATION AND SUSTAINED ENGAGEMENT:

RESULTS FROM TWO DISCRETE CHOICE CONJOINT EXPERIMENTS


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TITLE: Examining patient-preferred attributes to encourage mental health treatment initiation and sustained engagement: Results from two discrete choice conjoint experiments


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**ABSTRACT**

Mental illness places a large burden on individuals and society-at-large, a problem that becomes much worse the longer it is left untreated. Early intervention (EI) can mitigate this burden; however, those experiencing emerging mental illnesses often do not seek help promptly. Patient-centered care, such as shared-decision making models of mental healthcare, may reduce barriers to treatment. A central tenet of patient-centered care is that patient engagement and service utilization increases when patient preferences are incorporated into clinical services. In the current thesis, discrete choice conjoint experiments (DCE) were used to elicit the preferences of patients and their families, as well as the hypothesized preferences of patients according to mental health professionals, in two surveys. The first survey aimed to identify the attributes of an EI service that would encourage people experiencing psychiatric symptoms to initiate contact with a service and attend their first appointment (Chapter 2). The second survey sought to determine which service attributes would encourage someone to remain engaged with mental health treatment (Chapter 3). Both surveys used Latent Class Analysis to segment the study populations into identifiable subgroups based on shared preferences, and Randomized First Choice simulations to predict which service delivery model each of these identified groups would most likely use. The results of these studies have several implications for current and future mental health services. Effective EI mental health services should include rapid access to services, a range of treatment options, and

effective crisis response. Moreover, future DCE studies should focus on replicating these

results using more heterogeneous samples and improving DCE methods.

**DEDICATION**

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This thesis is dedicated to my fiancé, Peter Casurella.

Thank you for your love and support.

Your intelligence, sense of humor, and patience has made all of this possible.

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My graduate studies at McMaster University have been inspiring, educational, and fulfilling. I feel fortunate to have been surrounded by many wonderful people throughout this experience and to have joined such a formidable department. I owe my experiences throughout these past two years to many who deserve great thanks and acknowledgment.

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**PREFACE**

The purpose of this Master's thesis was to determine which attributes of an early

intervention (EI) mental health service would encourage treatment initiation and

sustained engagement. This research was motivated by the bourgeoning interest in

patient-centered care, particularly the incorporation of patient preferences into service

design and implementation. Additionally, the research was inspired by the use of

marketing research methodology in healthcare. Two conjoint surveys were formulated

with the purpose of asking two questions: what EI service attributes will increase the

likelihood of someone (1) initiating contact with an EI service and attending their first

appointment, and (2) remaining engaged in treatment. A literature search determined

which attributes would be the most relevant and important for conceptualizing an EI

service. These attributes were narrowed down with the help of focus groups, key

informant interviews, the expertise of the authors, and in the case of the second survey,

was also informed by the first survey's results. Each attribute was assigned four levels

and these multi-level attributes were formulated into the two aforementioned surveys that

were completed by mental health patients, their families, and mental health professionals.

Chapter 1 of this thesis contains a short overview of the research literature

investigating the benefits of EI services, some of the reasons why many patients may not

receive such services, and some potential strategies to enhance patients' initial contact

and ongoing engagement with such services. In particular, the central tenet of this thesis

is that patient engagement with EI services will be enhanced if service design considers

and incorporates the preferences of patients and their families with regard to the attributes

that characterize the service and its delivery. This hypothesis is explored using discrete

choice conjoint experimental (DCE) methods to identify important service attributes

regarding patient initiation and engagement. Given that DCEs are the central

methodology of this thesis, Chapter 1 also includes an introduction to these methods and

their unique benefits. Each of these service attribute questions posed above is addressed

in a separate survey and experiment. Therefore, the rationale, methods, results and

conclusions of each experiment are described in separate chapters (Chapters 2 & 3). It

should be noted that these two chapters are written in the form of stand-alone scientific

reports, each of which is about to be submitted for publication to peer-reviewed journals.

Finally, the thesis concludes with a General Discussion (Chapter 4), which attempts to

frame the two studies, and this line of inquiry more generally, in the broader research

literature and highlight their clinical and policy implications. It should also be noted that,

given that there exists substantial conceptual overlap between the two experiments and

the main issues described in both the General Introduction and General Discussion, the

reader may encounter some repetition throughout the thesis.

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## LIST OF ABBREVIATIONS

AIC – Akaike Information Criteria

AIC3 – Akaike Information Criteria 3

BIC – Bayesian Information Criteria

CAIC – Consistent Akaike Information Criteria

CRC – Colorectal cancer

EI – Early intervention

DCE – Discrete choice conjoint experiment

DUI – Duration of untreated illness

DUP – Duration of untreated psychosis

LCA – Latent class analysis

MDD – Major depressive disorder

MLE – Maximum likelihood estimation

PRPT – Partially randomized preference trials

QOL – Quality of life

RCT – Randomized controlled trials

RFC – Randomized first choice

SDM – Shared decision-making

TPB – Theory of planned behaviour

## DECLARATION OF ACADEMIC ACHIEVEMENT

**CHAPTER 1. General introduction: The problem and a proposed solution**

<u>Author</u>: Mackenzie P. E. Becker[1]

**CHAPTER 2. Early intervention mental health service preferences: A discrete choice conjoint experiment**

<u>Authors</u>: Mackenzie P. E. Becker[1], Bruce K. Christensen[1,2,4], Charles E. Cunningham[2,3], Ivana Furimsky[2,4], Heather Rimas[4], Fiona Wilson[2,4], Lisa Jeffs[4], Peter Bieling[2,4], Victoria Madsen[2,4], Yvonne Chen[2], Stephanie Mielko[2], Robert B. Zipursky[2, 4]

<u>Comments</u>: This manuscript was conceived by RBZ, CEC, and BKC. Data were collected and organized by IF, HR, FW, LJ, PB, VM, YC, and SM. Data for this study was analyzed by HR and MPEB. The manuscript was written by MPEB under the supervision of BKC, RBZ, and CEC.

**CHAPTER 3. Preferred attributes of early intervention mental health services: How patient-oriented service design can increase long-term engagement**

<u>Authors</u>: Mackenzie P. E. Becker, Charles E. Cunningham, Bruce K. Christensen, Ivana Furimsky, Heather Rimas, Fiona Wilson, Lisa Jeffs, Victoria Madsen, Peter Bieling, Yvonne Chen, Stephanie Mielko, Robert B. Zipursky

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<u>Comments</u>: This manuscript was conceived by RBZ, CEC, and BKC. Data were collected and organized by IF, HR, FW, LJ, VM, PB, YC, and SM. Data for this study was analyzed by HR and MPEB. The manuscript was written by MPEB under the supervision of BKC, RBZ, and CEC.

**CHAPTER 4. General Discussion**

<u>Author</u>: Mackenzie P. E. Becker

**CHAPTER 1**

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**GENERAL INTRODUCTION: THE PROBLEM AND A PROPOSED SOLUTION**

**Chapter 1**

The goal of this thesis is to study the patient-preferred attributes of early intervention (EI) services that would increase the probability of individuals with mental illness making initial contact and with remaining engaged in treatment over the long term. Before presenting the details of these studies, the following section attempts to position these objectives in a larger context. Specifically, it explores the burden of mental illness on affected individuals and society at-large, as well as how untreated mental illness can significantly worsen this burden. Next, barriers to treatment are examined in an attempt to understand why people with emerging psychiatric symptoms often do not receive EI services. Finally, some suggestions for potential solutions to increase patient engagement with EI services are provided, focusing specifically on approaches that emphasize patient-centered care and incorporating patient preferences into mental health service design.

**1.1 The burden of mental illness**

Mental illness affect**s** millions of people worldwide (Steel et al., 2014) and is one of the main causes of disability (*The world health report 2002: Reducing risks, promoting healthy life*, 2002). In particular, among various mental disorders, major depression, schizophrenia, social phobia, alcohol use disorders, and bipolar affective disorder are those with the greatest identified burden (Ratnasingham et al., 2013). This burden is expected to climb sharply in the coming decades. For example, in the year 2000, depressive disorders were considered the fourth leading cause of disease burden worldwide (Ustün, Ayuso-Mateos, Chatterji, Mathers, & Murray, 2004); however, it is

expected by the year 2020, that depressive disorders will be the leading cause of disease burden (Murray & Lopez, 1996). To understand the magnitude of the burden of mental illness, it is important to bear in mind that its negative impact is realized by both the affected individual (and his/her loved ones) (Maurin & Boyd, 1990; Tsang, Tam, Chan, Cheung, & Chang, 2003) as well as society at-large (Lim, Jacobs, Ohinmaa, Schopflocher, & Dewa, 2008; C. J. L. Murray & Lopez, 1996; Stephens & Joubert, 2001). These respective levels of illness burden are considered separately below.

**1.1.1 Individual burden.** Personal costs of mental illness include adverse life course transitions (e.g. school failure), reduced educational attainment, medical comorbidity, marital instability, low employment rates, and poverty (Christiana et al., 2000; Kessler et al., 2007, 2009; McGlashan, Miller, & Woods, 2001). Additionally, those with mental illness die significantly earlier than those without. Colton & Manderscheid (2006) compared the mortality of public mental health clients to those of their state's population. They found that clients with major mental illnesses were 1.2-4.9 times more at risk of dying, had between 13-30 years of potential life lost, and died 1-10 years earlier than the general population of the same geographical locations (Colton & Manderscheid, 2006).

Further compounding its associated burden is the fact that mental illness often has a much earlier age-of-onset than other medical conditions, such as cancer (Ratnasingham et al., 2013). For example, Kessler et al. (2005; 2007) reported that roughly half of Americans will experience a mental disorder and that the majority of those cases have their onset in their teens or early twenties (Kessler et al., 2005, 2007). Therefore, mental

illness typically occurs during developmentally sensitive periods, exaggerating its

negative impact (Kessler et al., 2009; McGorry, Purcell, Hickie, & Jorm, 2007).

Internationally prominent psychiatrist and EI researcher, Dr. Patrick McGorry points out:

> Given the exquisite developmental sensitivity of this phase of life, where
> psychological, social and vocational pathways and independence are being laid
> down, it is not surprising that mental disorders, even relatively brief and milder
> ones, can derail and disable, seriously limiting or blocking potential (McGorry et
> al., 2007, p. S5).

**1.1.2 Family burden.** The personal cost for the family of someone with a mental

illness is also high. Often, there is disruption to the lives of family members of someone

with mental illness (Maurin & Boyd, 1990), especially for caregivers (Benazon & Coyne,

2000; Coyne et al., 1987; Maurin & Boyd, 1990). The burden of providing care to a

mentally ill family member increases the probability that caregivers will also experience

emotional problems. For example, living with a depressed person was found to be

associated with a depressed mood in their spouses, as 6% of spouses met diagnostic

criteria for major depression and 14% had a history of depression (Benazon & Coyne,

2000). In this study, the three highest sources of spousal burden included the patient's

feelings of worthlessness, the possibility that the patient could become severely depressed

again, and the emotional strain on the spouse (Benazon & Coyne, 2000). Additional

stressors placed upon the family members of someone with a mental illness frequently

include the stigma towards people with mental illness, limited availability of public

resources, financial worry, isolation, and anxiety (Tsang et al., 2003).

**1.1.3 Societal burden.** The economic costs to society of mental illness are also

considerable (Lim et al., 2008; Stephens & Joubert, 2001). These include direct costs

such as treating mental illness (e.g., hospital and institutional care, lab tests, medications) and indirect costs (e.g., lost work productivity, disability, and death) (Greenberg & Birnbaum, 2005; Insel, 2008; Stephens & Joubert, 2001). Collectively, these expenses have been estimated to amount to over $14 billion annually in Canada (Stephens & Joubert, 2001) with some studies suggesting it may be closer to $51 billion (Lim et al., 2008). Moreover, those with mental illnesses have the highest utilization of all healthcare services (Lim et al., 2008) and receive the most disability income (Insel, 2008). The value of mental illness unemployment alone is estimated at approximately $32,750 per person per year in Canada (Lim et al., 2008).

**1.2 Untreated mental illness worsens the burden**

Given the high burden that mental illness places on individuals, their loved ones, and society, its detection, treatment, and management is a central priority. In this vein, the extent to which a mental illness goes undetected, untreated, or unmanaged has a negative impact on development, productivity and overall quality of life (QOL) is amplified (Harris et al., 2005; McGlashan et al., 2001). For example, a prospective longitudinal study examined the effect of duration of untreated psychosis (DUP) on the outcomes of 318 first-episode patients eight years after their initial treatment (Harris et al., 2005). A longer DUP, specifically longer than three months, predicted worse prognosis and outcomes, more severe symptoms, decreased quality of life, and poorer functioning (Harris et al., 2005). Other studies have suggested that reducing DUP in the prodromal phase of psychosis may improve outcomes and delay or prevent the onset of full-blown illness (McGlashan et al., 2001). Given that most mental disorders are

neurodevelopmental in nature, early diagnosis may pre-empt the onset of more severe symptoms and reduce morbidity (Insel, 2009). Developing biomarkers for early detection and diagnosis can help reduce the morbidity of illnesses such as schizophrenia or bipolar disorder, as this can preempt the development of more serious symptoms (Insel, 2009). In this vein, Insel (2009) compared the diagnosis of schizophrenia at the onset of psychosis to diagnosing cardiac disease once the patient has already had a heart attack (Insel, 2009). Cannon et al. (2008) found that certain pre-illness features can help predict whether an at-risk individual will go on to develop psychosis. These included genetic risk, substance abuse history and levels of unusual thought content, paranoia, and social impairment (Cannon et al., 2008). According to the authors, prediction algorithms that contained 2-3 of these features can increase predictive power in those identified as at-risk by 68%-80% (Cannon et al., 2008).

**1.3 EI can lessen the burden of mental illness**

The association between a shorter duration of untreated illness (i.e., the time between the emergence of symptoms/signs and receiving treatment; DUI) and better outcomes has led to a clinical and empirical groundswell of support to make EI practices a priority in mental healthcare (Harris et al., 2005). For years, EI in the form of genomics, imaging, and biomarkers, has been a common approach for treating other medical disorders (e.g., inflammatory bowel disease, cardiovascular disease, and cancer) (Insel, 2009) and is now gaining popularity as a best practice for the treatment of post-traumatic stress disorder (Bryant, 2007), borderline personality disorder (Chanen et al., 2009), psychotic disorders (Klosterkötter, 2011; McGlashan et al., 2001; Singh & Fisher, 2004;

Wong et al., 2012), and anxiety and mood disorders (Christiana et al., 2000), including bipolar affective disorder (Macmillan et al., 2007). The research base demonstrating the effectiveness of EI for treating mental disorders is also accumulating. For example, EI services for youth with psychosis can result in healthcare savings of £4,814 ($8,822.63 CAD) per patient, mostly in the form of reduced hospitalizations (McCrone et al., 2013). Wong et al. (2012) summarized the effects of EI services in Hong Kong since 2001, and found that overall, EI programs led to improved functioning, attenuated symptoms, reduced hospitalizations, and fewer suicides (Wong et al., 2012). Furthermore, the positive implementation of EI services in Hong Kong seems to have provided the impetus for further study into the area of EI (Wong et al., 2012).

**1.4 Reasons why many patients do not receive EI services**

Although EI is associated with improved clinical outcomes and QOL (Singh & Fisher, 2004), most mentally ill patients do not receive professional treatment until a number of years after illness onset (Christiana et al., 2000; Kohn, Saxena, Levav, & Saraceno, 2004; Macnaughton, 1998; Olfson, Kessler, Berglund, & Lin, 1998; Wang et al., 2005). The typical DUI is estimated to be 3 years for schizophrenia and 7-8 years for mood disorders (Macnaughton, 1998). Even after initiating treatment, there is continued risk for prolonged symptoms because accurate diagnosis during the early phases of mental illness can be difficult. According to Mcnaughton (1998), those with mood disorders waited an average of 13 years to get the correct diagnosis, while those with schizophrenia waited approximately 4 years (Macnaughton, 1998).

Research has also shown that, despite the serious nature of early-onset disorders, treatment programs tend to overlook these patients until the onset of more severe symptoms (Christiana et al., 2000). Christiana et al. (2000) examined delays in help-seeking in individuals with emerging psychiatric conditions. These authors studied data from 3,516 questionnaires completed by people involved in mental health patient advocate groups in 11 countries and found that less than half of respondents sought help within the first year of symptom onset. The mean delay was eight years for the majority of respondents, with the odds decreasing each year (Christiana et al., 2000). In an editorial, McGorry et al. (2007) note that this problem can be further complicated by the fact that illness severity typically drives the speed at which treatment services are accessed, suggesting that people with mental disorders must become progressively worse before they are considered for treatment (McGorry et al., 2007). This implies that there is a significant gap between onset and treatment for serious mental illnesses and that there is ample opportunity to intervene. However, in order to provide effective, comprehensive and accessible EI services, research must first address the reasons why patients are not currently accessing care in a timely manner (Macnaughton, 1998).

Resource limitations may be partly to blame for the long DUIs. Worldwide, almost one-third of countries have no mental health policies or implementation plans (Saxena, Thornicroft, Knapp, & Whiteford, 2007). Moreover, in 41 countries worldwide (26 of them low-income), there are no disability benefits for people with mental illness (Saxena et al., 2007). This situation is undoubtedly due to a variety of factors, including stigmatizing attitudes towards mental illness and inefficiency in the use of mental health

services (Saxena et al., 2007). Kohn et al. (2004) cite many additional factors that

contribute to the treatment gap in mental healthcare, including: a desire to deal with one's

illness autonomously, and the limited availability of needed services (Kohn et al., 2004).

Mcnaughton (1998) also lists various possible barriers to accessing care, including lack

of insight, fear, and minimization of the severity of their illness by healthcare workers

(Macnaughton, 1998). Lincoln & McGorry (1995) conducted a literature review to better

understand the various pathways to care for individuals with mental illness and suggest

that a more thorough understanding of the experiences of service users and more patient

involvement may increase knowledge surrounding access to mental healthcare (Lincoln

& McGorry, 1995). Ultimately, the goals of this thesis are in line with this observation

and seek to increase patient involvement as a means to increase service access. However,

in order to provide an appropriately broad perspective to understanding the multifaceted

reasons underlying barriers to appropriate care, the next sections briefly review important

illness-related, societal, and service-related factors that contribute to less than optimal EI

service access.

    **1.4.1 Stigma.** Stigma is a major barrier to accessing mental health treatment and

can be defined as "a sign of disgrace or discredit, which sets a person apart from others"

(Byrne, 2000, p. 65). Stigmatizing attitudes towards people who suffer from mental

illness are widely documented (Angermeyer, Matschinger, & Holzinger, 1998; Jorm,

2000; Link, Struening, Rahav, Phelan, & Nuttbrock, 1997; Nordt, Rössler, & Lauber,

2006; Schulze, Richter-Werling, Matschinger, & Angermeyer, 2003). Clinicians and

researchers alike suggest that stigma plays a role in why people do not seek help when

they experience psychiatric symptoms. For example, an empirical study examining help-seeking behaviours in 5,555 college students randomly selected from 13 schools found that stigmatizing attitudes were associated with lower levels of help-seeking (Eisenberg, Downs, Golberstein, & Zivin, 2009). Moreover, if a student perceived stigmatizing attitudes from others, they were less likely to approach a professor for support in the event of poor academic performance due to mental illness (Eisenberg et al., 2009). If one's stigmatizing attitudes were directed inwardly, the student was less likely to display treatment-seeking behavior, or to recognize a need for treatment at all (Eisenberg et al., 2009). These researchers concluded that attitudes can vary widely; thus, strategies aimed at reducing stigma should be tailored accordingly (Eisenberg et al., 2009). By reducing stigma, those with emerging psychiatric symptoms may be more likely to initiate contact with and engage in treatment services.

**1.4.2 Poor insight.** Poor insight is a common symptomatic feature of many mental illnesses and has been associated with non-adherence to a treatment program and with failing to initially seek treatment (Kreyenbuhl, Nossel, & Dixon, 2009). For example, Kessler and colleagues (2001) conducted a large cross-sectional survey to identify the rate of mental illness in the United States, as well as reasons those with mental illness do not seek treatment. They found that the majority of psychiatric patients who did not receive treatment did not believe they required it. For those who believed they did require treatment, many expressed a desire to solve their problems without assistance from others (again possibly owing, at least in part, to the stigma surrounding mental illness), a belief that their symptoms would spontaneously resolve, or a feeling

that treatment would be ineffective for their situation, as reasons for not seeking the appropriate services (Kessler et al., 2001). A more recent study found a link between having implicit positive attitudes towards medication and having increased illness insight (Rüsch, Todd, Bodenhausen, Weiden, & Corrigan, 2009). Thus it stands to reason that those who view psychiatric problems as an illness in need of treatment will be more likely to utilize services.

      **1.4.3 Wait times.** Another treatment barrier is the lag between the point at which someone makes initial contact with a service (e.g., making an appointment or placing an initial phone call) to treatment initiation (Foreman & Hanna, 2000; Kohn et al., 2004). For example, one study sent questionnaires to people on a waiting list for a child psychiatric clinic (Foreman & Hanna, 2000). Results showed that families are less likely to attend treatment programs if the wait is longer than 30 weeks (Foreman & Hanna, 2000). Others suggest that motivation for engaging in treatment may wane if families are not helped when they need it most (i.e., immediately after referral) and that this interim of untreated mental illness may increase the chances of symptom worsening and/or problematic behaviors (Westin, Barksdale, & Stephan, 2013). In a study examining how treatment engagement is affected by wait times, those who have to wait a longer time for services are less likely to begin treatment (Westin et al., 2013). Therefore, addressing barriers to treatment and fostering methods to encourage people with mental illness to seek help early in the course of their illness could further optimize the effectiveness of EI programs.

Stigma and wait times are societal and systems problems that are difficult to change. In addition, one study conducted on acutely psychotic patients with schizophrenia found that the same mechanisms associated with lack of insight may also be more likely to account for resistance to treatments (McEvoy et al., 1989). Therefore, while undoubtedly important, these factors may be difficult to affect in a meaningful fashion. However, as an augmentative approach, research suggests that increasing patient involvement and considering patient perspectives may result in greater service utilization (Swift, Callahan, & Vollmer, 2011).

**1.5 Patient-centered care**

One way to combat barriers to treatment is to enhance client involvement and client-provider communication (Swift et al., 2011), which are central tenets of patient-centered care practices (Delbanco, 1992). Patient-centered care is a multi-dimensional concept, and includes

> respecting patients' values, beliefs, and preferences; customizing care to the individual and making sure that care is culturally competent; and recognizing that patients' preferences may change over time and in response to shifts in clinical and other circumstances (Cook, 2005, p. 2).

It includes effective and efficient care, educating the patients with adequate and accessible information, involving the patients' family in the decision-making process, and meeting the treatment needs and values of the patient (Cook, 2005).

To achieve these goals, patient-centered care seeks to establish strong and trusting relationships between the patient and care provider, whereby the patient and their family members have input on health decisions based on their own personal values, priorities, and preferences (Epstein, Fiscella, Lesser, & Stange, 2010). This enables the clinician to

provide individually tailored and personalized care to the patient in order to maximally

address their needs (Epstein et al., 2010). Patient-centered care is also associated with

increased care efficiency. For example, Stewart and colleagues (2000) conducted an

observational cohort study to examine patient-centered care practices and the effects on

subsequent health service utilization. The researchers found that patients who viewed

their doctor visits as patient-centered were more likely to have improved clinical

outcomes and their healthcare was more efficient, given that the number of diagnostic

appointments were minimized (Stewart et al., 2000). The authors suggest that by

improving the patient's experience, their health is likely to improve as a result of their

perception (Stewart et al., 2000).

The inclusion of patients as collaborators in their healthcare has been increasingly

advocated in general medical settings (Hamann, Leucht, & Kissling, 2003; Karnieli-

Miller & Eisikovits, 2009; Youm, Chenok, Belkora, Chan, & Bozic, 2012) but is not yet

a standard in mental healthcare (Hamann et al., 2003). Nevertheless, the concept of

patient-centered care is increasingly viewed as having the same associated improvement

in mental health outcomes as seen in other healthcare domains (Epstein et al., 2010;

Stewart et al., 2000). The next section will review one of the primary frameworks for

incorporating patient-centered care into practice.

**1.5.1 Shared decision-making (SDM).** Research promoting patient participation

in clinical programming often employs a shared decision-making (SDM) model (Charles,

Gafni, & Whelan, 1997; Goossensen, Zijlstra, & Koopmanschap, 2007; Hamann et al.,

2003). Definitions of this model vary, but it is generally considered a compromise

between older, paternalistic models (e.g., the doctor uses his or her expertise to select a treatment plan, sometimes without consulting the patient at all) and informed choice models (e.g., the doctor informs patients of the options and decisions are made exclusively by the patients), wherein both parties discuss and decide upon treatment options (Charles et al., 1997; Hamann et al., 2003; Karnieli-Miller & Eisikovits, 2009). In SDM frameworks, the clinician provides expertise regarding clinical care options, and solicits the patient's input about how they would like to proceed (Goossensen et al., 2007; Hamann et al., 2003; Karnieli-Miller & Eisikovits, 2009). In other words, the goal of SDM is to enhance patient choice in relation to those aspects of healthcare that are most important to them (Hamann et al., 2003). There is evidence that mental health patients desire a more collaborative model of care. For example, a pilot study surveyed 30 adults with severe mental illness about decision-making regarding treatment (Adams, Drake, & Wolford, 2007). In regards to starting new medication, 39% of patients desired a more collaborative decision-making process than what they were currently receiving. Moreover, when compared to general medical care, those involved in psychiatric services were less inclined towards taking a passive role (23% compared with 76% in general medical care) (Adams et al., 2007). Moreover, 3,177 randomly assigned computer-assisted telephone interviews were conducted to determine patients' preference in regards to clinical decision-making. This study found that the majority of patients (62% of the sample) preferred SDM to styles such as paternalism (Murray, Pollack, White, & Lo, 2007). Interestingly, when asked how often they felt they had enough information to make an informed decision, only 11% of 3,187 respondents stated that they did all of the

time (Murray et al., 2007). Despite the benefits (Adams & Drake, 2006; Karnieli-Miller & Eisikovits, 2009) and increasing popularity of SDM (Hamann et al., 2003; Murray et al., 2007), it is not a standard practice in many areas of medicine (Ford, Schofield, & Hope, 2006; Karnieli-Miller & Eisikovits, 2009), including psychiatry (Adams & Drake, 2006).

**1.6 EI service design may be aided by the inclusion of patient preferences**

In the context of SDM, the inclusion of patient preferences in service design is purported to increase patient engagement. Patient preferences can reflect a range of concerns and priorities pertinent to treatment (Lang, 2005). These factors are important in determining patients' initiation and engagement with treatment since such decisions depend on how patients view the risks and benefits of potential treatment options (O'Connor et al., 2007). For example, patients may have an unrealistic expectation of a certain treatment, or a clinician may misjudge which aspects of care are of most value to the patient, which often results in an "overuse of treatment options that informed patients do not value" (O'Connor et al., 2007, p. 717). It is surmised that by adopting a collaborative approach and incorporating patient preferences into the design of mental healthcare services, providers can yield more personalized treatments that account for a range of circumstances and needs (Insel, 2009).

These assumptions are supported by preliminary mental health research. Swift and Callahan (2009) conducted a meta-analytic review on the data of 2,356 clients to determine whether the preferences of patients affect their treatment outcomes. Clients who had been matched to their preferred treatments had a 58% chance of greater

improvement (Swift & Callahan, 2009). Another meta-analysis, conducted to determine whether matching patients to their preferred treatments would influence dropout rates, found that clients who were matched to their preferred programs were half to a third less likely to drop out (Swift et al., 2011).

Treatment services that have incorporated patient choices have also increased the chances of depressed patients receiving treatments that they prefer and in turn, increased the rates of people entering and remaining engaged in treatment (Dwight-Johnson, Unutzer, Sherbourne, Tang, & Wells, 2001; Kwan, Dimidjian, & Rizvi, 2010). For instance, a study using a conjoint survey examined whether interventions for depression that incorporated patient and provider choice would increase rates of treatment initiation (Dwight-Johnson et al., 2001). These interventions increased the rates of initiating treatment by 50% compared with usual care (Dwight-Johnson et al., 2001). Moreover, a randomized clinical trial looked at the effects of treatment preference on attendance, dropout, working alliance, and improvement in the severity of depression (Kwan et al., 2010). Participants who were matched to their preferred treatment had a lower chance of dropping out, attended 89.1% of their appointments (compared to 84.9% attendance rate of those without preferences and 70.4% of those that were not matched), and had higher therapeutic alliance scores (Kwan et al., 2010). Therefore, it is anticipated that incorporating patient preferences into the design, development, and evaluation of mental health services may improve rates of initial contact and engagement with these programs.

**1.7 Methodological limitations**

While the preliminary research on the benefits of including patient choice and preference in mental health programming is promising, Swift et al. (2011) note several limitations in the current research. First, much of the research on preferences is conducted post-hoc, in an attempt to look at the effects of treatment (Swift et al., 2011). They suggest that it would be beneficial to gather preferences for treatment before the actual treatment occurs, so that services can be designed around preferences (Swift et al., 2011). Second, randomized controlled trials (RCT) are typically used to measure the effects of treatment, though these may not accurately account for preference effects as those who have the strongest preferences about treatment are less likely to volunteer for randomized studies of preference-based treatments (Swift et al., 2011). Partially randomized preference trials (PRPTs) attempt to rectify this, though they only compare patients who have stronger preferences to those with no preferences or weaker preferences (Swift et al., 2011). Third, none of the research that the authors reviewed accounted for other variables that could influence preferences or treatment dropout, such as gender, age, and background (Swift et al., 2011). Fourth, the studies did not measure the strength of preferences nor did they attempt to ascertain how participants might trade-off preferences when faced with choosing amongst a limited number of attributes (Swift et al., 2011). Therefore, while promising, this line of research could be strengthened by using methodological techniques aimed at rectifying these shortcomings. In this regard, discrete choice conjoint experiments (DCEs) are promising. In the next section, the primary features of DCEs and their application to ascertaining patient preferences with regard to healthcare service design are introduced.

**1.8 Conjoint analysis and DCEs**

Conjoint analysis and DCEs were developed as marketing research techniques, allowing for the design of a product with the most ideal attributes or characteristics (Curry, 1996; Orme, 2010). Conjoint analysis was developed in mathematical psychology (Luce & Tukey, 1964) and is a term that encompasses a variety of methods to elicit preferences and, as such, is typically used to describe any preference elicitation method that involves multi-level attributes (Louviere, Flynn, & Carson, 2010; Ryan & Farrar, 2000). There are many variations of conjoint analysis, and each has specific strengths depending on the number of attributes used in a study, how the survey or interview is administered, sample size, time to administer the survey or interview, and whether or not one is studying price (Orme, 2009).

DCEs have become commonly known as one form of conjoint analysis; however, according to Louviere et al. (2010), this is incorrect. Conjoint analysis is based on conjoint measurement, which is a method that analyzes the behaviour of numbers, not humans (Louviere et al., 2010). DCEs, on the other hand, are based on random utility theory (McFadden, 1973), which explains the choice behaviours of humans rather than numbers, and can better inform studies on human choice (Louviere et al., 2010). Moreover, DCEs are also influenced by the economic theory of value, which generally attempts to explain the value of certain products or services (Lancaster, 1966). DCEs are defined, therefore, as "an attribute based measure of benefit" (Ryan, 2004, p. 360) and are based on two assumptions: (1) that products or services are described by the various attributes that characterize them, and (2) that the choice or value one places on this

product or service depends on the multiple levels of the attributes (Ryan & Farrar, 2000; Ryan, 2004, p. 360). There are several important stages to conducting a DCE: (1) Define important attributes that characterize the service or product that is being conceptualized (Ryan & Farrar, 2000; Ryan & Gerard, 2003). This can be done by a variety of methods (e.g., literature reviews, focus groups) and depends upon the nature of the research being conducted (Ryan & Farrar, 2000). (2) Assign levels that describe the identified attributes (Ryan & Farrar, 2000; Ryan & Gerard, 2003). This depends on the attributes that are being used (i.e., cardinal, ordinal, or categorical) and should be chosen with feasibility in mind (Ryan & Farrar, 2000). (3) Combine these attribute levels into choice sets or scenarios (Ryan & Farrar, 2000; Ryan & Gerard, 2003). Typically, when completing a conjoint survey, one is presented with 2-3 scenarios or choice sets to choose between. These are comprised of attribute levels that are combined to describe a certain product or service. Figure 1.1 (below) illustrates an example of a choice set. (4) Establish the respondents' preferences (respondents choose the choice set that has the highest level of utility to them out of a variety of choice sets) (Ryan & Farrar, 2000, p. 1531; Ryan & Gerard, 2003). DCEs typically use surveys that pose forced-choice alternatives to respondents regarding certain attributes of a product or service (see Figure 1.1) and derive preferences from these trade-off situations or choices (Ryan & Farrar, 2000). (5) Analyze the data to determine preferences, using utility scores, importance scores, and other statistical techniques (Ryan & Farrar, 2000, p. 1531; Ryan & Gerard, 2003). These techniques will be further explained later.

*We are developing a new car. Choose which option you would be most likely to purchase*

*if you were looking for a new car.*

| $30,000 | $10,000 | $50,000 |
|---|---|---|
| Blue | Red | Red |
| 5 years average life | 10 years average life | 5 years average life |
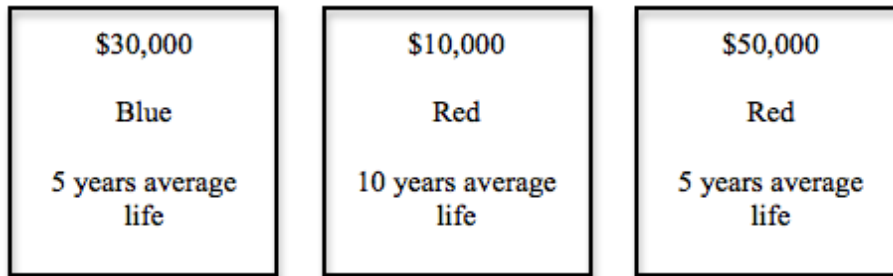
Figure 1.1 Example of a partial profile conjoint choice task. Partial profile is explained further below. In these conjoint choice tasks, participants would choose between hypothetical car options. Experimental designs can ensure that attribute levels are presented an equal amount of times. Moreover, experimental designs can also ensure that respondents are randomly assigned a survey version (Bridges et al., 2011; *The CBC advanced design module (ADM) Technical Paper*, 2008, *The CBC system for choice-based conjoint analysis*, 2013).

**1.8.1 An example.** Curry (1996) provides an example of using conjoint analysis to market a new golf ball, while Orme (2010) provides credit cards as an example (Curry, 1996; Orme, 2010). Using the general structure of Curry's (1996) and Orme's (2010) examples of consumer products, I will provide my own example of conjoint analysis using attributes of a new car to demonstrate the basic procedure and underlying logic of conjoint analysis.

**1.8.2 Attributes and levels.** When designing a new car, market researchers would first determine a few main features (or attributes) of this product; for example, price, colour, and average life of the car. Each of these attributes can be represented at multiple levels (see Table 1.1).

Table 1.1 Car attributes and levels

| Price | Colour | Average Life of the Car |
|---|---|---|
| $10,000 | Black | 5 years |
| $30,000 | Blue | 10 years |
| $50,000 | Red | 15 years |

Three attributes, each containing three levels, could yield 27 possible combinations.

An example of the selected combinations of attribute levels (i.e., design plan) (Orme, 2010) is shown in Table 1.2.

Table 1.2 Design plan

|  | $10,000 | $30,000 | $50,000 | Black | Blue | Red | 5 | 10 | 15 |
|---|---|---|---|---|---|---|---|---|---|
| Car 1 |  |  | X |  |  | X |  | X |  |
| Car 2 |  | X |  |  |  | X |  |  | X |
| Car 3 | X |  |  |  | X |  |  |  | X |
| Car 4 |  | X |  | X |  |  | X |  |  |
| Car 5 |  |  | X |  | X |  | X |  |  |
| Car 6 |  |  | X | X |  |  |  |  | X |
| Car 7 | X |  |  | X |  |  |  | X |  |
| Car 8 |  | X |  |  | X |  |  | X |  |
| Car 9 | X |  |  |  |  | X | X |  |  |

Partial profile conjoint analysis methods do not typically ask respondents to evaluate all possible combinations derived from the design plan at once (i.e., traditional full profile), as this would be overwhelming (Orme, 2010). A partial profile presents a subset of attribute levels describing a product or a service (Chrzan, 2010; Orme, 2010). In contrast, a full profile defines a product or a service using one level from every attribute in each choice set (Orme, 2010). In the car example, a full profile is used, as there are only three attributes; thus, all three attributes can be reflected in each product concept. Respondents may get confused or fatigued if they are asked to view product concepts

involving more than six attributes (Orme, 2010). A full profile design has the benefit of

being balanced. For example, each attribute level appears with every other attribute level,

allowing researchers to estimate the effect of each level independently (Orme, 2010).

This also allows researchers to formulate 9 different attribute combinations for this

product (see Figure 1.2).

Using these nine cards, respondents could then be asked to rate each offer on a

scale from 1 (do not like this offer at all) to 10 (love this offer) (Orme, 2010). It is important to note that DCEs are based on *choice*. In this example, ratings will be used simply to introduce the concept of conjoint analysis and how it can be used in DCEs overall. See Table 1.3 for an example of this.

| Car 1 | Car 2 | Car 3 |
|---|---|---|
| $50,000 Red 10 years | $30,000 Red 15 years | $10,000 Blue 15 years |

| Car 4 | Car 5 | Car 6 |
|---|---|---|
| $30,000 Black 5 years | $50,000 Blue 5 years | $50,000 Black 15 years |

| Car 7 | Car 8 | Car 9 |
|---|---|---|
| $10,000 Black 10 years | $30,000 Blue 10 years | $10,000 Red 5 years |

Figure 1.2 Different attribute combinations for a new car.

Table 1.3 Consumer A's rating

| Car | Rating |
|-----|--------|
| 1 | 0 |
| 2 | 2 |
| 3 | 3 |
| 4 | 9 |
| 5 | 3 |
| 6 | 6 |
| 7 | 7 |
| 8 | 8 |
| 9 | 4 |

In rating the different products, many individuals will adopt a strategy. For example, for one person, the colour red may be the most important attribute and they would, therefore, rate Cars 1, 2, and 9 with a score of 10, regardless of the other attributes (Orme, 2010). However, it is more likely that consumers would weigh each attribute more equally and make trade-offs based on the combination of the three levels (i.e., willing to trade off colour to get a cheaper car that will last a long time). Modeling these kinds of trade-offs closely reflect decision-making in the real world and represent a notable strength of DCE methods (Orme, 2010).

**1.8.3 Utility scores.** Using the consumer preference information (Table 1.3), ratings scores can generate values (otherwise called 'utilities', 'part-worths', or 'part-worth utilities') that depict what features the buyer is willing to trade-off for other, more important, features (Curry, 1996; Orme, 2010). Utilities can also be calculated using the data from a conjoint survey, utilizing choice tasks similar to Figure 1.1. However, for ease of understanding in this example, and due to a lack of actual survey data regarding purchasing a new car, utilities will be calculated using the ratings in order to demonstrate the basic principles and methods of conjoint analysis. In other words, conjoint analysis attempts to find the various preference weights assigned to each attribute (e.g., whether or not a consumer was rating cars based on the colour red) (Orme, 2010). Combining the individual attribute scores provides an overall utility score (Phillips, Johnson, & Maddala, 2002).

Orme (2010) presents a simple way to calculate utility scores for each option, which will be replicated here using the present car example. Conjoint analysis does not typically result in such basic calculations (Orme, 2010), though they will be kept simple in this example for ease of understanding. According to Orme (2010), using the ratings given for each attribute, part-worths can be easily calculated, as the utility estimate for each attribute level is the average for each of the cars that include that level. I will be using Consumer A's ranking scores to calculate the utility estimates (see Table 1. 4).

Table 1.4 Consumer A's utility scores

| Attribute Level | Ratings (0-10 scale) | | | Utility Score* |
|---|---|---|---|---|
| $10,000 | 3 | 7 | 4 | 14 |
| $30,000 | 2 | 9 | 8 | 19 |
| $50,000 | 0 | 3 | 6 | 9 |
| | | | | |
| Black | 9 | 6 | 7 | 22 |
| Blue | 3 | 3 | 8 | 14 |
| Red | 0 | 2 | 4 | 6 |
| | | | | |
| 5 | 9 | 3 | 4 | 16 |
| 10 | 0 | 7 | 8 | 15 |
| 15 | 2 | 3 | 6 | 11 |

* a higher utility score denotes a higher desirability for that level (Orme, 2010).

If marketers are attempting to decide on one product from several choices of products, conjoint analysis allows them to estimate consumer preferences based on the utility values and make predictions about which product a consumer would buy if they were given the choice (Curry, 1996). Based on Consumer A's utility scores in Table 1.4, one would assume that they would prefer a $30,000, black car that will last about 5 years. Incidentally, this describes Car 4 in Figure 1.2, which was given a rating of 9. One may ask why it is important to calculate these utility scores at all, given that the rating exercise

(Table 1.3) told us the same thing. Utilities are important in situations where a consumer

may give high ratings across the products.

Table 1.5 Consumer B's rating

| Car | Rating |
|-----|--------|
| 1 | 5 |
| 2 | 6 |
| 3 | 7 |
| 4 | 9 |
| 5 | 9 |
| 6 | 8 |
| 7 | 7 |
| 8 | 8 |
| 9 | 5 |

For example, it is entirely possible that Consumer B could have rated many of the cars highly, with little differentiation between the rating values (see Table 1.5). This would provide different utility scores for Consumer B (Table 1.6).

Table 1.6 Consumer B's utility scores

| Attribute Level | Ratings (0–10 scale) | | | Utility Score* |
|-----------------|------|------|------|----------------|
| $10,000 | 7 | 7 | 5 | 19 |
| $30,000 | 6 | 9 | 8 | 23 |
| $50,000 | 5 | 9 | 8 | 22 |
| | | | | |
| Black | 9 | 8 | 7 | 24 |
| Blue | 7 | 9 | 8 | 24 |
| Red | 5 | 6 | 5 | 16 |
| | | | | |
| 5 | 9 | 9 | 5 | 23 |
| 10 | 5 | 7 | 8 | 20 |
| 15 | 6 | 7 | 8 | 21 |

**1.8.4 Importance scores.** As noted above, based on Consumer B's utility scores,

B would prefer a $30,000 black or blue car that lasts about 5 years. While this is

surprisingly similar to Consumer A's preferences, there is one important difference: black

and blue are seemingly preferred equally. Colour could be an unimportant factor in

Consumer B's decision-making process, or it could be incredibly important. One way to

determine how important an attribute is to consumer choice is to calculate importance

scores (Orme, 2010). Importance scores "reflect the effect each attribute has upon

product choice, given the range of levels included" (Orme, 2010, p. 11). An example of

importance score calculations for Consumers A & B are included below in Tables 1.7 &

1.8.

Table 1.7 Consumer A's importance scores

| Attribute | Level | Utility Score* | Attribute Utility Range** | | | Utility Range Total*** | Attribute Importance **** |
|---|---|---|---|---|---|---|---|
| | | | Max | Min | Range | | |
| Price | $10,000 | 14 | | | | | (10/31)x100 |
| | $30,000 | 19 | 19 | 9 | 10 | | = |
| | $50,000 | 9 | | | | | 32 |
| Colour | Black | 22 | | | | | (16/31)x100 |
| | Blue | 14 | 22 | 6 | 16 | 31 | = |
| | Red | 6 | | | | | 52 |
| Average Life of the Car | 5 | 16 | | | | | (5/31)x100 |
| | 10 | 15 | 16 | 11 | 5 | | = |
| | 15 | 11 | | | | | 16 |

* Table 1.4
** An attribute's utility range is simply the largest score minus the smallest score
*** Price range + colour range + average life of the car range = utility range total
**** Utility range divided by utility range total multiplied by 100 to get a percentage

Table 1.8 Consumer B's importance scores

| Attribute | Level | Utility Score | Attribute Utility Range | | | Utility Range Total | Attribute Importance |
|---|---|---|---|---|---|---|---|
| | | | Max | Min | Range | | |
| Price | $10,000 | 19 | | | | | (4/15)x100 |
| | $30,000 | 23 | 23 | 19 | 4 | | = |
| | $50,000 | 22 | | | | | 27 |
| Colour | Black | 24 | | | | | (8/15)x100 |
| | Blue | 24 | 24 | 16 | 8 | 15 | = |
| | Red | 16 | | | | | 53 |
| Average Life of the Car | 5 | 23 | | | | | (3/15)x100 |
| | 10 | 20 | 23 | 20 | 3 | | = |
| | 15 | 21 | | | | | 20 |

Calculating importance scores demonstrates that colour is the most important attribute for both consumers (52% and 53%, respectively), while the average life of the car was much less so (16% and 20%, respectively) (Orme, 2010). Despite their different rankings of each car, it is possible to see which attribute levels are most preferred and which attributes are the most influential to each consumer when deciding on a product (Orme, 2010).

**1.8.5 Predicting preferences.** Thus far, nine potential cars have been evaluated using utility scores. These values can also be used to predict how much someone would prefer choice sets that were not given as options, also known as hold-out cards (Orme, 2010). For example, see Figure 1.3.

| Car 10 | Car 11 | Car 12 |
|--------|--------|--------|
| $50,000 | $30,000 | $10,000 |
| Black | Blue | Red |
| 10 years | 5 years | 15 years |

Figure 1.3 Choice sets not given as options.

First, you would add the part-worth utility values of each attribute level to get the value of each choice set. Consumer A's scores would be: 46 (Car 10), 49 (Car 11), and 31 (Car 12); Consumer B's scores would be: 66 (Car 10), 70 (Car 11), and 56 (Car 12). These predicted utility scores should closely resemble the scores that were calculated on the nine cars that the consumers evaluated (Orme, 2010). As hopefully demonstrated by this example, DCEs are an excellent way to solicit and evaluate preferences regarding products or services. In turn, service users are more likely to utilize specific products or services if they encompass attributes that they find desirable.

**1.9 From marketing research to healthcare**

**1.9.1 The use of DCE's in healthcare research.** DCEs were first developed as a tool for market and product research in order to solicit consumer preferences (Wittink, Vriens, & Burhenne, 1994). More recently, DCEs have been introduced into health economics as a way to go beyond simply exploring health outcomes (Ryan, 2004). In the same way that they drive product choice, preferences can also drive service engagement or satisfaction. Thus, DCEs can be used to ascertain preferred attributes of healthcare services, which should increase patient engagement. For example, DCEs can ascertain whether factors, over and above health outcomes (i.e., process outcomes: wait times,

service location, staffing), influence treatment utilization (Ryan, 2004). The use of DCEs have been increasing in healthcare over the past ten years, and as a result, a set of methodological standards have been proposed, including a checklist, that was designed to facilitate the ongoing application of conjoint analysis in healthcare (Bridges et al., 2011). There is also a report that aims to assist researchers in designing DCE designs (Johnson et al., 2013). DCEs allow researchers to estimate which aspects of healthcare are most preferred by users, uncover the trade-offs that people are making when deciding on treatment services, and estimate the utility each healthcare service is conferred given its attributes (Ryan & Farrar, 2000; Ryan, 2004).

DCEs have been employed to determine preferred attributes for a variety of health interventions and services (Ryan & Farrar, 2000). For example, Ryan (1999) determined that non-health outcomes and process attributes (e.g., attitudes of staff towards patient, continuity of contact with staff, time waiting on a list) were considered important by patients undergoing in vitro fertilization (Ryan, 1999). Similarly, Marshall et al. (2007) conducted a DCE survey of patients undergoing colorectal cancer (CRC) screening. The results showed that the majority of patients preferred noninvasive procedures and that CRC screening rates would increase if such preferences were incorporated as practice (Marshall et al., 2007). Marsidi, van den Bergh, & Luijendijk (2014) used conjoint analysis to determine the importance of attributes that are involved in choosing an aesthetic private surgical clinic. Their results indicated that 150 patients stated that the experience of the surgeon (35.6% importance score) and the method of referral (21.5%)

were the two most important attributes for those choosing an aesthetic private clinic

(Marsidi et al., 2014).

**1.9.2 The use of DCEs in mental healthcare research.** Along with medical

healthcare, DCEs and conjoint analysis have begun to be used in mental healthcare as

well. A 2004 study examined the use of conjoint analysis in measuring treatment

preferences of people with depression, specifically Latino patients with low incomes

(Dwight-Johnson, Lagomasino, Aisenberg, & Hay, 2004). The patients generally

preferred a combination of medication, counseling, and individual treatment. They also

determined that telephone appointments and bus passes would likely reduce barriers to

care (Dwight-Johnson et al., 2004). DCE experiments have revealed that service design

factors may also play a role in mental health utilization. Cunningham and colleagues

(2008) conducted a DCE to elicit preferences of parents who were seeking information

on mental health services for their children. Latent class analysis (LCA; discussed further

below), was used to identify subgroups of participants that were characterized by similar

preferences. The authors found three segments within their study population and

conducted simulations to predict how many parents within each segment would actually

use the information strategies provided to them. For example, 61.7% of the *Information*

segment would likely choose a program that included evidence-based readings on

childhood issues that were recommended by their therapist. The majority (88.5%) of the

*Action* segment would likely choose a program that was paced according to the individual

and focused on solutions, while 88.8% of the *Overwhelmed* segment would prefer to wait

for treatment services to become available (Cunningham et al., 2008).

**1.10 Advantages of DCEs over other methods**

DCEs and conjoint analysis are excellent methods for eliciting and evaluating

preferences for attributes of a product or a service. This information can be used to

determine what is important to patients and family members and, as a result, be employed

to enhance service uptake, determine which service will be best utilized in the future, and

reduce barriers to care. Beyond this, DCEs also have many advantages over other rating

and survey methods.

Forced-choice approaches, such as conjoint analysis, engage participants in real-

world decision-making heuristics, quantify and reveal hidden biases, differentiate

between attributes, highlight what is actually driving preferences, rectify some of the

limitations in current research on patient preferences, and utilize powerful statistical

methods to thoroughly examine patient preferences. Below is a review of each of these

advantages.

**1.10.1 Force people to engage in real-world decision-making heuristics.** In the

car example, ratings were used to determine which cars people would prefer. It is

important to note that this rating exercise was used in conjunction with utility and

importance scores. When ratings-based methods are used alone, some problems can arise.

In comparison to ratings-based methods of preference solicitation, conjoint surveys result

in a greater likelihood that respondents will engage in heuristics used in real world

decision-making (Caruso, Rahnev, & Banaji, 2009; Shah & Oppenheimer, 2008).

Heuristics seek to reduce the strain caused by decision-making, and allow a person to

arrive at a decision with reduced difficulty (Shah & Oppenheimer, 2008). In other words,

conjoint analysis methods force the respondent to make trade-offs between attributes (Orme, 2010). Rating or ranking surveys do not typically engage this type of decision-making, as there is the option to rank all of the attributes similarly, rather than deciding between them. In the real-world, it is often impossible to design and/or implement services that encompass all of the most desirable qualities; as such, concessions must be made. In forcing someone to trade certain attributes for others, researchers can determine which attributes are essentially driving the choice (i.e., are the most important or influential; see turtle vs. mermaid shaped-pool example below). In forcing someone to trade certain attributes for others, researchers are able to determine which attributes are most important and can then gain a better understanding of what people really want in a service or a product (Orme, 2010).

**1.10.2 Quantify and reveal hidden biases.** Conjoint analysis allows for the measurement of biases as people's attitudes may unconsciously lead them to choose one attribute over another (Caruso et al., 2009). For example, if someone is buying a pool, they may not know how important either 'shape or 'price' may be in their decision-making. Thus, they may not be able to state or consciously access how much they are willing to pay given a pool's shape. Instead, they may be more able to decide that they prefer a mermaid shaped pool for $10,000 to a turtle shaped pool for $8,000. In making this choice (all else being equal), they are valuing a mermaid shaped pool at least $2,000 more than one that is shaped as a turtle.

In a DCE study conducted by Caruso et al. (2009), researchers were able to reveal hidden biases based on attributes that had originally been deemed less important by the

participants. The researchers asked students to imagine they were choosing a prospective teammate for a trivia game (Caruso et al., 2009). These teammates varied on education, IQ, experience with trivia games, and body weight (Caruso et al., 2009). While three of the dimensions had to do explicitly with how successful one would be in the trivia game, importance scores suggested that weight played a large role in who was chosen for a teammate (Caruso et al., 2009). Conjoint analysis is a method in which each attribute level is given a utility score to determine how much each attribute level is preferred over the others. It is then possible to determine which attributes are most influential in one's decision-making by computing importance scores (Caruso et al., 2009). The majority of participants preferred a thin teammate to a heavy one, despite the participants stating that they did not consider weight an important factor. In this regard, participants would trade an average of 11 IQ points to have a thinner teammate, without realizing they had done so (Caruso et al., 2009).

**1.10.3 Differentiate between attributes.** Another advantage offered by conjoint methods is the ability to differentiate between attributes. Rating or ranking surveys can be troublesome as they will often produce high scores across all of the positive attributes of a product or service, reflecting people's desire to 'have it all' (Orme, 2010). Furthermore, if a service has received high scores across all of the attributes, there is very little differentiation between the choices that were presented (Orme, 2010). In contrast, DCEs and conjoint analysis reflect a more realistic decision-making approach, by forcing the consumer to make concessions in decision-making, thus allowing the researcher to learn the true value of product alternatives (Orme, 2010).

Conjoint analysis methods can reveal the trade-offs that are made during decision-making and estimate how important attributes are in relation to others, which can be very useful if researchers are trying to determine what kind of service or product to offer, but have limited resources (Ryan & Farrar, 2000). In utilizing the information that is provided by conjoint methods, services can be designed with the most important attributes prioritized (Ryan & Farrar, 2000), which is a much more feasible endeavor than trying to design a service from a rating survey wherein *all* of the positive attributes have been ranked quite highly and no trade-offs have been made. In making this task more feasible, preferred services can more easily be implemented, and patient engagement may increase as a result.

**1.10.4 Illuminate true decision-making motives.** In the context of increasing service uptake, choice methods can also bring to light what may be driving someone's decision-making, even if they are unaware of it. Phillips et al. (2002) measured attitudes and preferences for HIV tests; thus, they used a rankings/rating survey and conjoint analysis to compare the two approaches. There were differences between the findings depending on the approach (Phillips et al., 2002). Price was a significant factor according to the conjoint methods, but was seen to be less important in the attitude measure. For example, a respondent stated that he did not want to appear cheap by rating price as important in the survey. However, his answers to the conjoint tasks revealed that much of his decision-making was based on price (Phillips et al., 2002).

Moreover, the attitude measurements are more susceptible to "halo effects" in which the valuations of one attribute affect how the others are evaluated as well. With

conjoint methods, respondents evaluate combinations of attribute levels (i.e., various

scenarios), whereas in methods that measure attitudes, respondents measure attributes

holistically (e.g., rather than determining that $100 is preferable to $200, they would

simply evaluate the importance of 'price') (Phillips et al., 2002). Caruso et al. (2009)

state that people tend to be better able to order their preferences when they are required to

evaluate choice options conjointly as this removes the task of determining how important

isolated attributes are when making a decision (Caruso et al., 2009).

Finally, there were inconsistencies among the responses given in the conjoint

approach.  Many respondents chose to focus on one attribute specifically (e.g., price), and

base all of their choices around it, attempting to simplify the decision-making process

(Phillips et al., 2002). This could result in preferences being less accurate. Internal

validity evaluation measures, such as hold-out tasks, can discreetly and easily be

implemented within a conjoint survey. Hold- out tasks are identical choice tasks that are

included in the survey – though not in the preference results – to determine how

consistent responses are. By simply measuring how many respondents gave the same

answer to the identical choice tasks, predictive validity can be determined in a

quantifiable way and inconsistent respondents can be identified (Johnson & Orme, 2010).

**1.10.5 Rectify limitations in current research on patient preferences.** As noted

above, Swift et al. (2011) highlight some limitations in the research literature on patient

preferences (Swift et al., 2011). I will now describe how conjoint analysis and DCEs

address many of these limitations. First, much of the research conducted on preferences is

done post-hoc, as researchers wish to focus on the effects of treatment (Swift et al.,

2011). Conjoint methods allow for preferences to be easily determined before treatment begins, allowing for a service to be designed around the preferences. In doing so, more effective services will be designed, uptake may be enhanced, and researchers can determine whether particular service designs are more beneficial to patients over others.

Second, typically RCTs have been used to measure treatment effects, though they typically do not account for preference effects (Swift et al., 2011). For example, people with strong preferences will likely not agree to be in a randomized setting where they may be matched to a non-preferred treatment (Swift et al., 2011). PRPTs have been able to rectify this somewhat, though these trials only have the ability to compare those with strong preferences to those with none or weaker preferences (Swift et al., 2011). As described extensively in this chapter, conjoint analysis is able to determine which attributes and levels are most strongly preferred.

Third, Swift et al. (2011) could not find preference research that included moderator variables (e.g., gender, age) that may influence preferences or treatment engagement. In analyzing conjoint survey results, it is fairly straight forward to include covariates such as age or gender into the analysis to ascertain their influence (Lanza & Rhoades, 2013).

Fourth, many of the studies did not include a measure of the strength of preferences (Swift et al., 2011). As a result, researchers were unable to determine whether the strength of preferences could affect treatment dropout (Swift et al., 2011). For instance, if a patient strongly preferred one treatment over another, this could lead to a higher likelihood of dropping out of treatment if they were not matched to their

preferred service (Swift et al., 2011). Conjoint analysis methods and DCEs are able to use

utility values and importance scores to determine the strength and influence of each

attribute and attribute level, which can then be used to determine how preferences can

effect treatment engagement or dropout.

     **1.10.6 Statistical analytical procedures.** The data derived from DCEs can be

analyzed in several ways. Below, I will outline some of these procedures and how they

can contribute to interpreting the results derived from DCEs.

**1.11 Latent Class Analysis (LCA)**

     Conjoint data can not only determine preference utility and importance scores, it

can also be analyzed in such a way so as to segment the study population using LCA.

Wittink, Vriens, & Burhenne (1994) discovered that product development using conjoint

analysis began growing in Europe in the early 1990's. The authors suggested that in order

to stimulate the growth of conjoint analysis, identifying characteristics that require a

certain approach (i.e., segmentation of the market) would be beneficial (Wittink et al.,

1994). The conventionally used method to segment a study population based on similar

preferences (LCA) is explored further below.

     **1.11.1 What is LCA?** LCA stems from latent class theory, which states that

unobserved clustering variables "can be inferred from a set of categorical indicators"

(Lanza, Savage, & Birch, 2010, p. 836). LCA is a statistical method that is used to

identify unobservable segments, or latent classes, of people within a study population

(Lanza, Collins, Lemmon, & Schafer, 2007) "based on a set of indicators and examining

the relations between individual characteristics and subgroup membership" (Lanza et al.,

2010, p. 834). Typically, two parameters are estimated: (1) the probability of being in a class, and (2) the probability of responding a certain way to an item that is conditional on being a member of that class (Lanza et al., 2007). The responses in a conjoint survey can be submitted to LCA in order to identify segments or clusters participants that are grouped by similar preferences (Lanza & Rhoades, 2013).

**1.11.2 How is LCA conducted?** LCA uses several information criterion to determine how many latent classes a particular dataset should ideally retain (Dziak, Coffman, Lanza, & Li, 2012; Nylund, Asparouhov, & Muthén, 2007), including Akaike information criteria (AIC), Akaike information criteria 3 (AIC3), Bayesian information criteria (BIC), and consistent Akaike information criteria (CAIC) (Lanza & Rhoades, 2013). According to Lanza & Rhoades (2013), each model under consideration should specify multiple sets of random starting seeds. This is to "confirm that a solution does not reflect suboptimal estimates caused by a local, as opposed to global, mode (maximum of the likelihood function)" (Lanza & Rhoades, 2013, p. 160). If a solution is identified for many of the starting seeds, then the maximum likelihood solution has likely been identified (Lanza & Rhoades, 2013).

Maximum likelihood estimation (MLE) is used for parameter estimation (Myung, 2003). According to the principle of MLE,

> the desired probability distribution is the one that makes the observed data ''most likely'', which means that one must seek the value of the parameter vector that maximizes the likelihood function (Myung, 2003, p. 93).

A balance between model fit and parsimony is indicated by a lower value for each information criterion (Lanza & Rhoades, 2013).

Segment membership probabilities represent the number of people estimated to belong within each latent subgroup (Lanza et al., 2010) and sum to one. Item-response probabilities are parameters that associate each response item (e.g., conjoint choice task) with each segment, allowing for the interpretation of LCA (Lanza et al., 2010). Adding covariates into the analysis creates odds ratios depicting the odds of someone belonging in a particular subgroup based on the covariates that have been added (e.g., age, sex) (Lanza et al., 2010).

**1.12 Randomized First Choice (RFC) simulations**

Once preferences have been established, along with segment membership, another way to analyze conjoint data is to estimate how much utilization a particular service may get from each latent group. This can be done with Randomized First Choice (RFC) simulations.

**1.12.1 What is RFC?** The part-worth utilities from the conjoint data can be used to determine how much usage a particular product or service may get based on the conjoint survey results (*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*, 2003). Particular combinations of attribute levels can form a hypothetical service which conjoint simulation software can then simulate using the DCE data. This assesses "attribute importance and sensitivities, complex interaction or substitution effects, and the likely success of products given certain competitive conditions" (*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*, 2003, p. 1). Doing so can help determine which service would be the best to implement, or how a specific service would fare in comparison to another given a

specific sample of users (*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*, 2003).

**1.12.2 How are RFCs conducted?** RFC simulations begin with the first choice or maximum utility rule. This rule assumes that the option with the highest composite utility (i.e., the option with the highest utility values) will be someone's 'first choice' (Orme & Huber, 2000). For example, if someone were once again deciding on a car, and had two attributes, price and colour, to help make their decision, they may give part-worth utilities seen in Table 1.9.

Table 1.9 Part-worth utilities for price and colour attribute levels of a car

| Attribute Level | Partworth Utilities |
|---|---|
| $10,000 | 0 |
| $30,000 | 40 |
| $50,000 | 30 |
| Blue | 25 |
| Black | 50 |
| Red | 0 |

Using the first-choice rule, one would predict that this particular consumer's first choice is a $30,000 black car (90 utiles).

However, this rule fails to take into account any random factors that may alter one's preferences in a real-world decision-making scenario (Orme & Huber, 2000). For example, a $30,000 black car may be an individual's first-choice; however, there may be no black cars in stock, forcing that individual to ultimately choose a blue car.

RFC recognizes that there are mitigating factors surrounding decision-making at the individual level, and, using first-choice as a starting point, adds variability to each utility value. RFC ensures that any mitigating factors are taken into account by adding adequate error and by sampling each respondent several times (typically 200,000 times) in order to stabilize the estimates of preference shares (*Advanced Simulation Module*

*(ASM) for product optimization v1.5 (Technical paper)*, 2003; Orme & Huber, 2000). In

doing so, RFC also has the ability to correct for product similarity due to correlated sums

of errors among services that may be comprised of many of the same attributes. RFC

does this by splitting preference shares exactly for identical products (*Advanced*

*Simulation Module (ASM) for product optimization v1.5 (Technical paper)*, 2003).

**1.13 Summary of the problem and proposed solution**

In summary, mental illness causes tremendous hardship for affected individuals

and their families. In addition, it results in significant economic and social burden for

society at-large. The longer a mental illness goes undetected and untreated, the higher

this burden is likely to become. EI may mitigate some of the negative outcomes

associated with mental illness. However, people do not typically seek help promptly

following the onset of their symptoms. Given the potential positive impact of EI services,

it is imperative that mental healthcare systems research methods to facilitate EI. An

important reason underlying people's reluctance to contact and/or utilize mental health

services may relate to feeling uninvolved in one's own care. Moreover, research has

demonstrated greater engagement in services that incorporate patient preferences with

regards to service attributes. Thus, it stands to reason that soliciting preferred attributes

for EI services and incorporating these attributes into service design should increase

engagement with EI services. In order to accomplish this goal, however, valid methods

for soliciting patient preferences and priorities are needed.

Conjoint analysis and DCEs represent promising methods to determine what

service users actually desire in an EI program. These methods are rooted in market

research and have recently begun to be used in health and mental healthcare as a way to include the needs and priorities of patients in policy-making and service design. DCE and conjoint analysis methods offer many advantages over more traditional survey methods and address many of the weaknesses to which previous preference research was susceptible. DCEs can be subjected to advanced statistical methods such as LCA, which can segment a study population into groups based on shared preferences. This can have implications for designing individually tailored treatment services aimed at these distinct groups and may enhance uptake. Moreover, even before implementing individualized services, researchers can use RFC simulations to determine which services would get the most utilization and which services would be the best to implement.

The current thesis analyzed the results of two DCE surveys which were administered to patients, their family members, and mental health professionals in an attempt to understand a variety of perspectives in regards to EI service design and implementation (Holley, Hodges, & Jeffers, 1998). Research suggests that engagement in mental health treatment involves two steps that should be studied separately: treatment initiation and continued treatment (Westin et al., 2013). Therefore, in the first survey, we sought to identify EI service attributes that would maximize the likelihood that people with mental health problems would contact a service (i.e., make initial contact and attend their first appointment). The second survey sought to highlight important EI service attributes that are likely to increase the chances of someone remaining engaged with treatment over time. The following two chapters (2 & 3) will present these studies in detail.

**CHAPTER 2**

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**EARLY INTERVENTION MENTAL HEALTH SERVICE PREFERENCES: A**

**DISCRETE CHOICE CONJOINT EXPERIMENT**

**2.1 Abstract**

**OBJECTIVE**: Early intervention (EI) for mental illness may improve outcomes; however, it is often difficult to engage people in treatment. Collaborative healthcare incorporates preferences to improve engagement. A Discrete Choice Conjoint Experiment was used in Canada to identify EI service attributes encouraging engagement.

**METHODS**: 16- 4 level attributes were formalized into a survey, completed by patients, their families, and mental healthcare professionals (N=562), asking which healthcare option people would contact. Latent Class Analysis identified segments characterized by shared preferences. The attribute blend resulting in the most utilization was predicted using Randomized First Choice simulations.

**RESULTS**: The *Conventional Service* segment (44%) thought people would contact traditional services (e.g., located in a hospital, staffed by psychologists/ psychiatrists). Membership was associated with being a patient/ family member and male. The *Convenient Service* segment (56%) thought patients would contact services promoting easy access (e.g., self- referral, accessed from home). Both thought patients would be most likely to contact services that included short wait times, direct contact, patient autonomy, and psychological treatment information. The *Convenient Service* segment estimated that patients would utilize an *E-Health* model while the *Conventional Service* segment thought patients would use either *Primary Care* or a *Clinic/ Hospital* based model.

**CONCLUSIONS**: Patient utilization of EI services may be increased by providing a range of services based on the attributes highlighted in this study. Moreover,

professionals may be more apt to adopt EI service models in line with their preferred attributes; thus, a range of perspectives is important to consider in service design.

*Keywords*: early intervention, collaborative healthcare models, discrete choice conjoint analysis, latent class analysis, health professional preferences, patient preferences, and mental health services.

**2.2 Introduction**

Relative to most medical disorders, mental illness is considered the most burdensome (Ratnasingham et al., 2013). Its negative impact is compounded by high prevalence and early onset (Ratnasingham et al., 2013). Nearly 50% of Americans will experience a lifetime mental disorder and about 75% of adult psychiatric cases have their onset before age 24 (Kessler et al., 2007). The poor outcomes observed in mental illness become exacerbated the longer it goes undetected or untreated (Kohn, Saxena, Levav, & Saraceno, 2004). Treating those with emerging disorders promptly can mitigate this problem (Conus & Mcgorry, 2002). Consequently, there has been growing interest in the potential for early intervention (EI) to improve functioning (Chanen et al., 2009), reduce rates of suicide/ hospitalization (Wong et al., 2012), and prevent the full expression of disorders (Kessler et al., 2007) . However, most patients do not receive treatment until a number of years after illness onset (Kohn et al., 2004), once more severe symptoms emerge (Christiana et al., 2000; Kessler et al., 2007). Moreover, attitudinal barriers, structural barriers and poor insight into the need for treatment are potential further obstacles to patient engagement (Andrade et al., 2013).

Therefore, despite the importance of EI, it is often difficult to engage patients in timely and specialized services, making it imperative that mental healthcare investigate ways to facilitate patient engagement. An empirically demonstrated means of improving engagement is to incorporate patients' preferences regarding service features (Swift, Callahan, & Vollmer, 2011). Although including patients as collaborators is associated

with advantages, it has rarely been incorporated into models of mental health service delivery (Hamann, Leucht, & Kissling, 2003).

Here, it is argued that the inclusion of patient preferences in EI service design may increase the rates at which symptomatic individuals access such services. Collaborative approaches may augment help-seeking among those experiencing emerging symptoms. For example, patients matched to their preferred treatments often have reduced drop-out rates and improved outcomes (Swift et al., 2011; Swift & Callahan, 2009). Thus, incorporating preferences in EI mental health services may increase rates of initial contact with these programs. However, valid methods for soliciting preferences are needed.

The Discrete Choice Conjoint Experiment (DCE) has been employed to solicit preferences for numerous health interventions (Ryan, Gerard, & Amaya-Amaya, 2007). DCEs pose forced-choices regarding multi-level attributes (see Table 2.1 for the current study's attributes) of a product/service and derive preferences from these choices (Orme, 2010). DCEs mimic the trade-offs that occur in real-world decision-making, and offer advantages over traditional survey methods (Caruso, Rahnev, & Banaji, 2009; Orme, 2010). Ratings often produce high scores across attributes, reflecting people's desire for services that encompass *all* positive characteristics. Resource limitations, however, frequently necessitate trade-offs between attributes (Orme, 2010). Furthermore, conventional surveys cannot differentiate between the preference for the level of an attribute and its relative importance, whereas DCEs can use choice data to quantify an attribute's importance (Orme, 2010).

This study used a DCE to elicit the views of patients, their families, and mental health professionals, pertaining to the attributes of an EI service they thought people with psychiatric illnesses would most likely contact. Although it is obvious why one would solicit the opinions of patients, it may be less clear why the other respondents also completed the surveys. Understanding multiple service design perspectives is advantageous. For instance, a service that patients use needs to incorporate their preferences to ensure uptake and continued engagement (Swift et al., 2011; Swift & Callahan, 2009). Furthermore, the adoption of new practices by professionals may be affected by their varying preferences and attitudes (Aarons, 2004). Modeling a successful program, therefore, needs to balance the views of users with those who provide services. Areas in which both parties agree could form a foundation for individual treatment and illness management; discrepancies could facilitate planning strategies and detect areas that may require service innovations (Holley, Hodges, & Jeffers, 1998).

Three research questions (RQ) were asked:

*RQ1. Can respondents be represented by latent classes based on similar EI service preferences? If so, what EI attributes are the most influential for decision-making across these segments?*

*RQ2. Do the segments differ in regards to demographic covariates?* Three covariates that could influence EI service preferences were examined: background (patients/ family members vs. professionals) (Holley et al., 1998), age (Robb, Haley, Becker, Polivka, & Chwa, 2003), and sex (Afifi, 2007) of the respondents.

*RQ3. Do the different segments differ regarding how and where EI services are delivered?* Simulations were conducted to predict the percentage of survey respondents who would likely utilize an EI service based in an (1) e-health, (2) primary care, or (3) a clinic/hospital setting.

**2.3 Method**

**2.3.1 Participants**. The St. Joseph's Healthcare Hamilton Research Ethics Board approved this study. Participants were recruited from nine sites. Overall, 562 people completed the survey (249 patients, 92 family members, and 221 professionals), ranging in age from 16- 75+. As long as the conjoint section was complete, the respondents were included in the analysis. As such, there were 548 fully complete surveys, and 14 with some missing data. In total, 583 patients/ family members were asked about the survey, and 341 completed it (58.5% return rate); 488 professionals were asked, and 221 completed the survey (45.3% return rate).

**2.3.2 Survey development.** The study design was informed by the International Society for Pharmacoeconomics and Outcomes Research (ISPOR) checklists (Bridges, Hauber, et al., 2011; Johnson et al., 2013). A literature search was conducted to identify important attributes. Overall, 16 4-level EI service attributes were derived, and categorized into five groups (see Table 2.1). At the beginning of the survey, terms that may have been unclear to respondents, such as "mental health problems" were defined.

Sawtooth Software's SSI Web (version 7.0.4) was used to administer the computerized survey (Vermunt & Magidson, 2005). A partial profile design (i.e., each forced-choice task includes only a subset of the attribute options) was employed to avoid

the presentation of all attribute levels at once and to improve response efficiency by simplifying the tasks presented (Chrzan, 2010; Orme, 2009). In 18 choice tasks, participants chose between three hypothetical EI service options (Figure 2.1 represents a sample choice task), and was asked to select the EI service, comprised of specific combinations of attribute levels, they thought patients would contact. The experimental design ensured that each attribute level was presented as close to an equal number of times as possible, and generated 999 versions of the survey. Each respondent was randomly assigned a version (Bridges, Hauber, et al., 2011; *The CBC advanced design module (ADM) Technical Paper*, 2008, *The CBC system for choice-based conjoint analysis*, 2013). Demographic variables were also collected (see Table 2.3 in the 'Results' section).

*We are developing a new service that encourages people with mental health problems to get help quickly.*

*Click below the service people would be most likely to contact.*

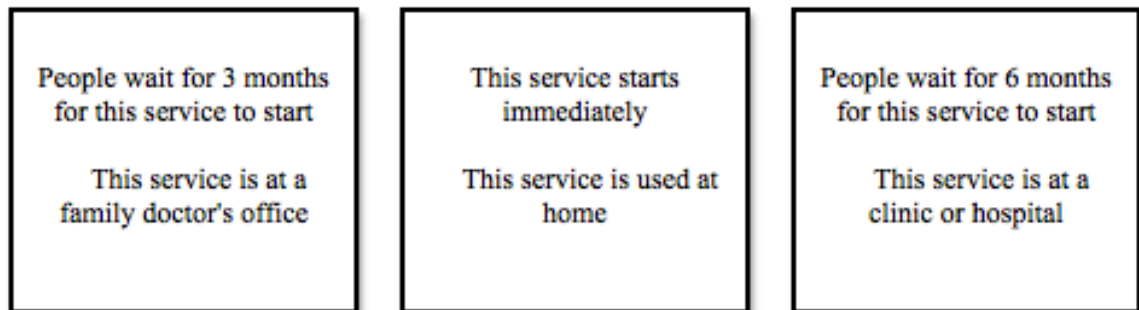| People wait for 3 months for this service to start<br><br>This service is at a family doctor's office | This service starts immediately<br><br>This service is used at home | People wait for 6 months for this service to start<br><br>This service is at a clinic or hospital |
|---|---|---|

Figure 2.1 Sample conjoint survey choice task. 18 choice tasks were made up of the experimentally varied combinations of the 16-4 level attributes. In each task, participants were asked to select the hypothetical EI service option that they would most prefer if contacting an EI mental health service for the first time.

**2.3.3 Procedure.** Research assistants approached reception staff to ask whether patients and family members arriving at the clinics would be willing to consider participating in the computerized survey. Professionals were asked to complete the survey via an emailed link. Following a complete description of the study, written, informed consent was obtained. Upon completion, each participant was given a choice of $15.00 gift cards.

**2.3.4 Statistical analysis.** Latent Gold Choice 4.5 software (Vermunt & Magidson, 2005) was used to analyze the conjoint survey data. Latent Class Analysis software clusters survey respondents into segments based on similar preferences (Lanza & Rhoades, 2013). Different information criteria were used to determine which maximum likelihood solution (i.e., the ideal number of latent classes) to adopt (Lanza & Rhoades, 2013). A lower value for each information criterion denotes a balance between model fit and parsimony (Lanza & Rhoades, 2013). Latent class solutions that included one to five solutions were modeled. Each solution was replicated ten times from random starting seeds. Background (Holley et al., 1998), age (Robb et al., 2003), and sex (Afifi, 2007) were included as covariates as these were predicted to have an impact on one's likelihood of contacting an EI service (Collins & Lanza, 2010).

Zero-centered utility coefficients were computed to determine how strongly each attribute level (i.e., which option) was preferred. Z scores are associated with the utility coefficients[1]. Importance scores[2] reflect how much effect variations in the levels of each

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[1] Any Z-scores that are higher than 1.96 or lower than -1.96 are considered statistically significant.

attribute exert on choice (Orme, 2010). An initial concern was the ability of some

individuals to respond to choice tasks as they may be seen as complicated; however,

research suggests that conjoint methods effectively solicit the opinions of those with

serious mental illnesses (Bridges, Kinter, Schmeding, Rudolph, & Muhlbacher, 2011).

The estimated preferences (i.e., what participants thought patients would want in an EI

service) from conjoint surveys can be used to simulate each respondent's likelihood of

choosing a specific service (*Advanced Simulation Module (ASM) for product

optimization v1.5 (Technical paper)*, 2003). Randomized First Choice (RFC) simulations

begin by adding variability to each part-worth score and simulating each person's

responses 200,000 times (i.e. sampling iterations), which are subsequently averaged

(*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*,

2003; Huber, Orme, & Miller, 1999; Orme & Huber, 2000). RFC takes mitigating factors

into account (i.e., perhaps someone wants Service A, but has to go with Service B as A is

too expensive); thus, simulations can estimate preference shares that are more

representative of the types of decision-making that occur in real-world situations

(*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*,

2003). This is because RFC predicts the response of participants to complex multi-level

attribute options that they are likely to encounter (Huber et al., 1999; Orme & Huber,

2000).

**2.4 Results**

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[2] Importance scores are calculated using the range in utility coefficient scores (maximum
less minimum utility) (Orme, 2010).

**2.4.1 RQ1.** Latent Gold Choice 4.5 was used to determine whether latent classes - i.e., underlying segments characterized by similar preferences (Lanza & Rhoades, 2013) - exist within the choice data (Vermunt & Magidson, 2005). We chose the two-class model that minimized the Bayesian Information Criteria [BIC] (Nylund, Asparouhov, & Muthén, 2007). The goal was to obtain distinct subgroups from a relatively large sample size; thus, BIC seemed to be the most appropriate to use (Dziak, Coffman, Lanza, & Li, 2012).

Both segments thought patients would contact an EI service that: starts immediately, incorporates direct contact, allows people to talk to a service provider from their own culture, and only takes one hour for the first appointment. Moreover, both segments predicted that people would be most likely to contact a service that provides information regarding psychological treatments and has been endorsed by those who have experienced mental health problems.

Utility coefficients (Table 2.1) show that the first segment (44% of the sample) thought people with mental health problems would be more likely to contact an EI service that was located at a clinic/ hospital, staffed by psychiatrists/ psychologists, and was available to anyone 18 years of age or older. In addition, this segment recommended that the service be advertised at events within the community and offer appointment scheduling at convenient times for both the patient and the service. This segment was sensitive to variations in the background of the service providers - favoring psychiatrists and psychologists over less traditional providers, assessment format (i.e. contact by phone, internet, etc.), and the opinions of people who have experienced mental illness

and deemed this service helpful. This group was labeled the *Conventional Service* segment.

Segment 2 (56% of the sample) thought patients would be more likely to contact a service that was: open to walk-in, accessed from respondents' homes, open to self-referral, available to anyone 12 years of age or older, staffed by mental health nurses, and advertised on radio and television. Importance scores (Table 2.2) show that this segment was more sensitive to variations in wait times, level of family involvement, and the referral process. Because of the emphasis on ease of access, this group was labeled the *Convenient Service* segment.

Table 2.1 Zero-centered utility coefficients and Z values for the *Conventional Service* and *Convenient Service* segments

| Attribute | Latent Class Segment | | | | |
| | Conventional | | Convenient | | |
| Attribute Levels | U | Z | U | Z | *Wald* |
|---|---|---|---|---|---|
| **Making Initial Contact with the Service** | | | | | |
| **EI service advertising format** | | | | | 38.91[c] |
| This service is not advertised | -0.11 | -0.96 | -1.22 | -8.61 | |
| This service is advertised on television & radio | -0.02 | -0.16 | **0.44** | **4.39** | |
| This service is advertised at public awareness events in the community | **0.45** | **4.35** | 0.42 | 4.34 | |
| This service is advertised on internet sites like Google, Facebook, or Twitter | -0.32 | -2.50 | 0.36 | 3.47 | |
| **Referral process** | | | | | 82.36[c] |
| People can refer themselves | -0.07 | -0.52 | **1.44** | **11.97** | |
| People must be referred by school counselors, family doctors, or mental health professionals | 0.05 | 0.48 | -0.02 | -0.17 | |
| People must be referred by family doctors or mental health | **0.16** | **1.56** | -0.22 | -1.92 | |

professionals

| | | | | | |
|---|---|---|---|---|---|
| People must be referred by a mental health professional | -0.14 | -1.17 | -1.20 | -8.34 | |
| **Wait times** | | | | | 21.85[c] |
| This service starts immediately | **1.27** | **11.16** | **2.12** | **14.04** | |
| People wait for one month for this service to start | 0.23 | 2.07 | 0.83 | 6.04 | |
| People wait for 3 months for this service to start | -0.52 | -4.18 | -0.44 | -2.92 | |
| People wait for 6 months for this service to start | -0.98 | -6.46 | -2.51 | -7.85 | |
| **Appointment scheduling** | | | | | 12.90[b] |
| Appointments at a convenient time for the service | -0.28 | -2.41 | -0.87 | -6.86 | |
| Appointments at a convenient time for patients | 0.12 | 1.15 | 0.17 | 1.69 | |
| Appointments at a convenient time for both patients and the service | **0.26** | **2.42** | 0.34 | 3.55 | |
| No appointments needed - can be used anytime | -0.10 | -0.90 | **0.36** | **3.65** | |
| **Time demand for first contact** | | | | | 7.83 |
| First contact takes 1 hour | **0.56** | **4.94** | **0.53** | **5.46** | |
| First contact takes 2 hours | 0.21 | 1.90 | 0.36 | 3.75 | |
| First contact takes 3 hours | -0.34 | -2.79 | 0.01 | 0.07 | |
| First contact takes 4 hours | -0.43 | -3.45 | -0.90 | -7.24 | |
| **Context of the EI Service** | | | | | |
| **Location** | | | | | 58.92[c] |
| This service is used at home | -0.30 | -2.10 | **0.35** | **3.49** | |
| This service is at a shopping mall or store front | -1.57 | -7.01 | -0.53 | -4.79 | |
| This service is at a family doctor's office | 0.66 | 5.31 | 0.20 | 2.03 | |
| This service is at a clinic or hospital | **1.21** | **9.11** | -0.01 | -0.08 | |
| **Atmosphere** | | | | | 9.43[a] |
| This service feels like it is for people aged 12 to 18 | -0.50 | -4.20 | -0.91 | -7.23 | |
| This service feels like it is for people aged 19 to 25 | -0.34 | -2.95 | -0.39 | -3.66 | |
| This service feels like it is for people aged 18 and older | **0.65** | **6.01** | 0.60 | 5.83 | |
| This service feels like it is for people aged 12 and older | 0.18 | 1.54 | **0.70** | **6.70** | |

| | | | | | |
|---|---|---|---|---|---|
| **Professional background of service providers** | | | | | 20.63 [c] |
| People talk to someone who has experienced a mental illness | -0.38 | -3.08 | -0.57 | -4.49 | |
| People talk to a mental health nurse | -0.11 | -1.03 | **0.50** | **5.11** | |
| People talk to a social worker | -0.25 | -2.20 | -0.20 | -1.91 | |
| People talk to a doctor (psychologist or psychiatrist) | **0.74** | **7.23** | 0.26 | 2.66 | |
| **Cultural background of service providers** | | | | | 13.99 [b] |
| Culture is not considered when assigning service providers | -0.08 | -0.73 | -0.75 | -5.82 | |
| If they want, people talk to service providers from their culture | **0.44** | **4.44** | **0.81** | **8.48** | |
| If the service decides, people talk to a service provider from their culture | -0.11 | -1.00 | 0.09 | 0.91 | |
| People always talk to service providers from their culture | -0.24 | -2.14 | -0.15 | -1.48 | |
| **Format of service contacts** | | | | | 7.51 |
| Contact is by text messages | -0.95 | -6.36 | -1.33 | -9.00 | |
| Contact is at an internet site | -0.62 | -4.56 | -0.25 | -2.28 | |
| Contact is by phone | 0.38 | 3.53 | 0.58 | 6.04 | |
| Contact is face-to-face | **1.20** | **10.65** | **1.00** | **9.65** | |
| **Service Decision Making** | | | | | |
| **Decisions regarding anonymity** | | | | | 17.74 [c] |
| People don't give their name when contacting this service | -0.15 | -1.33 | 0.18 | 1.81 | |
| If they want, people give their name when contacting this service | **0.29** | **2.79** | **0.68** | **6.82** | |
| The service decides whether people need to give their name when contacting this service | -0.10 | -0.94 | -0.11 | -1.10 | |
| People must give their name when contacting this service | -0.03 | -0.32 | -0.75 | -5.57 | |
| **Decisions regarding family involvement** | | | | | 43.07 [c] |
| Families are not involved | -0.52 | -4.30 | -1.23 | -7.54 | |
| If the service wants, families are involved | 0.08 | 0.80 | 0.10 | 0.93 | |
| The service and people using the service decide if families are | **0.34** | **3.02** | **1.42** | **12.24** | |

involved

| | | | | | |
|---|---|---|---|---|---|
| Families are always involved | 0.09 | 0.82 | -0.28 | -2.48 | |
| **Provided by the Service** | | | | | |
| **Information about Rx options** | | | | | 5.43 |
| Does not give information about treatment options | -0.98 | -6.77 | -1.23 | -8.61 | |
| Gives information about alternative treatments (e.g. diet, exercise, etc.) | 0.43 | 4.10 | 0.52 | 5.21 | |
| Gives information about psychological treatments | **0.47** | **4.44** | **0.82** | **7.78** | |
| Gives information about medications | 0.08 | 0.68 | -0.11 | -1.02 | |
| **Internet social networking options** | | | | | 61.65 [c] |
| No internet social networking options | -0.13 | -1.19 | -1.02 | -5.98 | |
| Has an unsupervised internet site where people talk about mental health problems | -0.36 | -3.14 | -1.31 | -7.33 | |
| Has a professionally supervised internet site where people talk about mental health problems | **0.32** | **3.23** | **1.17** | 9.58 | |
| Has an internet site where professionals answer questions about mental health problems | 0.17 | 1.56 | 1.16 | **9.61** | |
| **Raising awareness within the community** | | | | | 19.68 [c] |
| This service does not educate the community about mental health | -0.57 | -4.39 | -1.30 | -8.91 | |
| Once a year this service educates the community about mental health | -0.37 | -3.06 | -0.55 | -4.70 | |
| Once a month this service educates the community about mental health | 0.37 | 3.63 | 0.73 | 7.57 | |
| Once a week this service educates the community about mental health | **0.56** | **5.19** | **1.12** | **11.22** | |
| **Evidence of Service Efficacy** | | | | | |
| **Content evidence based** | | | | | 12.78 [b] |
| We do not know if this service is helpful | -0.77 | -5.72 | -1.32 | -9.07 | |

| | | | | |
|---|---|---|---|---|
| People who have experienced mental health problems say this service is helpful | **0.45** | **4.22** | **0.90** | **9.13** |
| Mental health professionals say this service is helpful | 0.39 | 3.87 | 0.25 | 2.56 |
| Research says this service is helpful | -0.07 | -0.65 | 0.17 | 1.66 |

*Note.* U = Utility coefficient values that have been zero-centered. Stronger preferences are indicated by higher utility coefficient values (Orme, 2010).

Z = Z scores associated with the utility coefficients. Any Z-scores that are higher than 1.96 are considered statistically significant and denote a significantly preferred attribute level.

The highest utility coefficients and z-values within each latent class segment have been bolded.

[a] = p< 0.05 ; [b] = p<0.01; [c] = p<0.001.

Table 2.2 Standardized importance scores for the *Conventional Service* and *Convenient*

*Service* segments

| | Latent Class Segment | | | |
|---|---|---|---|---|
| | Conventional | | Convenient | |
| EI Service Attributes | R | I | R | I |
| **Making Initial Contact with the Service** | | | | |
| Wait times | 5 | 6.55 | 1 | **14.32** |
| Referral process | 9 | 5.36 | 3 | **8.20** |
| Appointment scheduling | 11 | **4.14** | 14 | 3.82 |
| EI service advertising format | 14 | 2.93 | 9 | **5.14** |
| Time demand for first contact | 16 | 1.61 | 12 | **4.45** |
| **Context of the EI Service** | | | | |
| Professional background of service providers | 1 | **15.00** | 15 | 3.30 |
| Format of service contacts | 2 | **12.20** | 6 | 7.22 |
| Cultural background of service providers | 7 | **6.13** | 11 | 4.83 |
| Location | 8 | **6.05** | 16 | 2.73 |
| Atmosphere | 15 | 2.39 | 10 | **4.99** |
| **Service Decision Making** | | | | |
| Decisions regarding anonymity | 6 | **6.22** | 13 | 4.41 |
| Decisions regarding family involvement | 10 | 4.64 | 2 | **8.22** |
| **Provided by the Service** | | | | |
| Internet social networking options | 4 | **7.78** | 4 | 7.69 |
| Information about Rx options | 12 | 3.70 | 8 | **6.33** |
| Raising awareness within the community | 13 | 3.69 | 5 | **7.49** |
| **Evidence of Service Efficacy** | | | | |
| Content evidence based | 3 | **11.63** | 7 | 6.86 |

*Note.* R = Within each segment, the attribute's importance has been ranked from 1-16, with 1 being the most important. Within each subheading, the attributes have been organized according to the most important to least important for the *Conventional Service* segment.

I = Importance score of each attribute for the two latent class segments. Importance scores are expressed as percentages. The higher importance score between the two segments have been bolded. Attributes with higher importance scores are considered to have more influence on decision-making in regards to EI service preferences (Orme, 2010).

**2.4.2 RQ2.** Demographic information for the survey and the two segments are summarized in Table 2.3. Parameter estimates for the covariates (U) reflect the strength of the relationship between the covariates and membership within each segment[3].

Membership in the *Conventional Service* segment was associated with being either a patient or family member (U= 0.40, Z= 5.42, p<0.001) and a male (U= 0.23, Z= 3.43, p<0.001). Conversely, membership in the *Convenient Service* segment was associated with being a mental health professional and female. Age was not a significant covariate (U= +/- 0.01, Z= +/-0.10, p= 0.92) and, therefore, not discussed further.

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[3] i.e., a – sign indicates that that particular variable level is not associated with segment membership.

Table 2.3 Demographic variable percentages for the latent class segments

| | N | Total | Latent class segment | | $\chi^2$ |
| | | | Conventional | Convenient | |
|---|---|---|---|---|---|
| Sample Size | 562 | 100 | 241 | 321 | |
| Background | | | | | $94.7^{***}$ |
| Patient/ Family members | 341 | 60.7 | 83.8 | 43.3 | |
| Professional | 221 | 39.3 | 16.2 | 56.7 | |
| Age | | | | | $14.8^{**}$ |
| 16-20 | 36 | 6.6 | 11.2 | 3.2 | |
| 21-35 | 149 | 27.1 | 24.5 | 29.1 | |
| 36-55 | 278 | 50.6 | 48.1 | 52.5 | |
| 55+ | 86 | 15.7 | 16.3 | 15.2 | |
| Sex | | | | | $50.0^{***}$ |
| Male | 158 | 28.8 | 44.6 | 17.1 | |
| Female | 391 | 71.2 | 55.4 | 82.9 | |
| Education | | | | | $46.2^{***}$ |
| High school or less | 102 | 18.6 | 31.8 | 8.9 | |
| Greater than high school | 446 | 81.4 | 68.2 | 91.1 | |
| Birth country | | | | | $7.7^{**}$ |
| Born in Canada | 455 | 82.9 | 77.7 | 86.7 | |
| Born in another country | 94 | 17.1 | 22.3 | 13.3 | |
| Language | | | | | 4.9 |
| English | 486 | 88.5 | 86.3 | 90.2 | |
| French | 6 | 1.1 | 2.1 | 0.3 | |
| Other | 57 | 10.4 | 11.6 | 9.5 | |

$^{*}$ = p< .05; $^{**}$ = p<.01; $^{***}$ = p<.001

**2.4.3 RQ3.** RFC simulations were computed using the individual utility coefficients[4] generated by Latent Gold Choice 4.5 (Vermunt & Magidson, 2005). RFC simulations use the conjoint data to predict the percentage of respondents that would utilize a service comprised of a particular combination of attributes (*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*, 2003; Huber, Orme, & Miller, 1999).

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[4] *Note.* Individual utility coefficients were used for this section of the analysis, whereas the rest of the data presented was aggregate utility coefficients 6/23/14 8:36 AM.

One of the study's focuses was to explore emerging healthcare options that may encourage early utilization, as well as determine the attractiveness of the existing healthcare models. Three EI service options were created: (1) *E-health* involved: (a) being used from home, (b) self-referral, (c) no appointments, (d) Internet advertising, (e) service contact at an Internet site, (f) people can decide whether to give their name, and (g) an Internet site where professionals answer questions about mental illness. (2) *Primary Care* involved: (a) service at a family doctor's office, (b) self-referral, and (c) appointment scheduling convenient for both parties. (3) *Clinic/Hospital* involved: (a) service at a clinic or hospital, (b) family doctor or mental health professional referral, and (c) appointments based on convenience to the service. The *Primary Care* and *Clinic/Hospital* options shared many similarities: (a) no advertising, (b) face-to-face contact, (c) no option for withholding one's name, and (d) no Internet social networking options.

The RFC results (Table 2.4) show that the *Conventional Service* segment was split, with 44.2% predicting that patients would be more likely to use the *Primary Care* model and 42.3% the *Clinic/ Hospital* model. In contrast, 96.1% of the *Convenient Service* segment thought patients would be most likely to utilize the *E-Health* option.

Table 2.4 Randomized First Choice (RFC) simulations

| | Total | | Latent Class Segment | | | |
| | | | Conventional | | Convenient | |
| | % | SE | % | SE | % | SE |
|---|---|---|---|---|---|---|
| **EI Service Simulation** | | | | | | |
| E-Health | **60.7** | 1.8 | 13.5 | 1.2 | **96.1** | 0.4 |
| Primary Care | 21.1 | 0.9 | **44.2** | 0.4 | 3.8 | 0.3 |
| Clinic/ Hospital | 18.2 | 1.0 | 42.3 | 1.1 | 0.2 | 0.03 |

*Note.* RFC simulations predict the percentage of survey respondents in the latent classes that would utilize each hypothetical EI mental health service model (Orme & Huber, 2000).

*% =* Percentage of participants in the total sample and in each segment that would likely prefer each model.

*SE =* Standard error (U/Z).

The most preferred EI service model option for the total sample and for each latent class segment has been bolded.

Participants completed three fixed choice tasks. The purpose of the first was to introduce survey tasks and the other two were identical (i.e., "hold-out" tasks) (Bridges et al., 2011; Johnson & Orme, 2010). The discrepancy between observed and simulated mean absolute errors (MAE)[5] was 4.86 for the first task and 7.03 for the second; thus acceptable predictive validity can be concluded.

**2.5 Discussion**

**2.5.1 RQ1.** A DCE was used to determine attributes of an EI service that mental health care patients, their family members, and professionals would be most likely to contact. These methods have been borrowed from marketing research (Orme & Huber, 2000) and are relatively new to mental health (Ryan, Gerard, & Amaya-Amaya, 2007). The two segments that were identified predicted that patients would contact services with minimal wait times, patient autonomy, psychological treatment information, and endorsements from other service users. The *Conventional Service* segment (44%) thought that patients would be more likely to contact EI services that included mutually convenient appointments at a clinic or hospital. They were sensitive to variations in

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[5] The standard error difference of the hold-out tasks that each person completed and a simulation (i.e., predicting what each respondent will choose) were calculated 6/23/14 8:36 AM. In general, a lower number is better, though there is not a standard MAE discrepancy.

professional background. The *Convenient Service* segment (56%) thought that people with mental illness would be apt to contact EI services that were easy to access and use (e.g., self-referral to a service that one can walk to or use from home). This segment was sensitive to variations in wait times. Interestingly, neither segment seemed interested in information about medication, consistent previous research using a DCE (Cunningham et al., 2013). Interestingly, another study found a link between increased illness insight and positive attitudes towards medication (Rüsch, Todd, Bodenhausen, Weiden, & Corrigan, 2009).

**2.5.2 RQ2**. The results suggest that patients and family members differ in their responses from those of professionals. This may imply that people experiencing psychiatric symptoms would contact an EI service that differs significantly from services that mental health professionals think they would contact. Other research has shown the same pattern (Holley, Hodges, & Jeffers, 1998). A collaborative model of healthcare should be made a priority, and future EI services designed with a variety of perspectives in mind. As such, services may become more effective for patients, as future designs will reflect their specific priorities, alongside professional expertise. The conjoint results differed significantly by gender as well, further highlighting the need to incorporate a variety of perspectives in service design.

**2.5.3 RQ3.** Simulations determined that the *Conventional Service* segment was divided in their estimation of which service model people with mental health problems would use: a *Primary Care* or a *Clinic/ Hospital* model. The *Convenient Service* segment thought those with mental health problems would utilize the *E-Health* option for service

delivery. Importantly, an appointment made based on convenience to the service was an attribute that yielded negative utility. Although this is the current reality of most specialized services, it may affect the results of this simulation.

## 2.6 Implications

Providing a range of service options may improve utilization of EI services among patients. Simulations predicted that providing only one EI service will be unlikely to meet the needs of a broad range of patients as well as remaining consistent with the attitudes of mental health professionals.

Higher rates of contacting a specific service will likely follow whichever service delivery model had the lowest wait times given the importance placed upon this attribute. Both segments placed emphasis on services with no wait times and minimal time demand, suggesting a need for faster access to services. A strong relationship between wait times and the likelihood of failing to attend one's initial appointment has been found (Gallucci, Swartz, & Hackerman, 2005). In one study, the rate of kept appointments was significantly impacted with each day of delay for the first week (Gallucci et al., 2005), suggesting that those who can obtain prompt psychiatric care will be more likely to attend their initial appointment ((CPA), 2006; Gallucci et al., 2005).

Both segments also had high utility scores for service attributes that underscored autonomy, suggesting that mental health patients may prefer a collaborative healthcare model in which they have input regarding which services will best suit their individual needs (Hamann, Leucht, & Kissling, 2003).

## 2.7 Limitations

The survey asked respondents to answer the choice tasks from the perspective of someone accessing EI services for the first time; however, they were not all in that situation. Many of the participants were service users already involved in – and likely more accepting of – traditional service models. Experienced service users have a knowledgeable perspective and are considered valuable by youth (Cunningham et al., 2013); however, anyone objecting to traditional services would probably not have been involved in the study. This sample was somewhat older than the group of patients who are typically the focus of EI services. This sample may not accurately reflect the needs of a younger group of people seeking services for the first time. Age was not observed with segment membership; thus, it is not linked to the pattern of results regarding EI service attributes seen in this paper. Future studies should include samples in need of, but not yet involved in, treatment services.

A greater range of attribute levels could lead to different results, which could also vary based on different contexts. For example, the attributes that influence whether people will access a mental health service may not inform whether they will remain in a treatment program. This question is the focus of a second study described in Chapter 3.

## 2.8 Conclusions

Designing an EI service that maximizes utilization by people with emerging mental illnesses requires a strategy that considers a range of options. E-health and more traditional approaches to EI services will likely maximize help-seeking between divergent groups which is essential given the results identified within our sample. This approach would be more beneficial than a service targeting specific segments or

combinations of attributes. It may also enhance uptake and adherence by targeting a

wider range of people. EI services should maximize choice and patient autonomy as

much as possible consistent with the current trend for collaborative models of healthcare.

**CHAPTER 3**

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**PREFERRED ATTRIBUTES OF EARLY INTERVENTION MENTAL HEALTH**

**SERVICES: HOW PATIENT-ORIENTED SERVICE DESIGN CAN INCREASE**

**LONG-TERM ENGAGEMENT**

**3.1 Abstract**

**OBJECTIVE:** Discrete Choice Conjoint Experimental methods were used to identify patient-preferred early intervention (EI) attributes that encourage ongoing service engagement.

**STUDY DESIGN AND SETTING:** 333 patients/ family members and 183 professionals (N=516) completed a survey consisting of 18 choice tasks comprised of 14-4 level attributes. Preference impact on decision-making was ascertained using importance and utility scores. Latent Class Analysis identified two segments characterized by shared preferences. Randomized First Choice (RFC) simulations were used to estimate utilization of hypothetical services.

**RESULTS:** Both segments rated having treatment options and crisis response services as the most influential attributes. The *Collaborative* segment (53%) consisted mostly of professionals and indicated that engagement could be enhanced with: weekday evening appointments, one-on-one and group sessions, and help available by text or phone. The *Expert* segment (47%) consisted mostly of patients and family members and indicated that weekday afternoon appointments, sessions alone with a clinician, and phone help would encourage sustained engagement. Simulations predicted 69.4% of the *Collaborative* segment would utilize an *E-health* service whereas 60% of the *Expert* segment would use a *Hospital* model.

**CONCLUSION:** Important attributes were shared by both segments. Future EI services may involve many models of care but should include these attributes to facilitate long-term patient engagement.

*Keywords:* early intervention, discrete choice conjoint experiments, latent class analysis,

health professional preferences, patient preferences, and mental health services.

**3.2 Introduction**

Mental illness places an enormous burden on individuals and society at-large (Kessler et al., 2009; Lim, Jacobs, Ohinmaa, Schopflocher, & Dewa, 2008; Stephens & Joubert, 2001). This burden is significantly increased when affected persons do not receive early intervention (EI; timely treatment soon after the emergence of clinical symptoms) (Wang et al., 2005). For example, EI mental health services have been associated with reduced hospitalizations (McCrone et al., 2013; Wong et al., 2012), attenuated symptom severity (Wong et al., 2012), faster clinical improvement (Chanen et al., 2009), and, in some cases, recovery (Malla, Norman, & Voruganti, 1999). Conversely, the negative effects of mental illness are amplified when disorders go untreated (Harris et al., 2005; Kessler et al., 2007; Larsen, McGlashan, & Moe, 1996). Although EI may mitigate the burden of mental illness and improve clinical outcomes (Chanen et al., 2009; Kessler et al., 2007; Malla et al., 1999; McCrone et al., 2013; Wong et al., 2012), many people with emerging symptoms do not receive timely treatment (Christiana et al., 2000; Kessler et al., 2001; Kessler, Olfson, & Berglund, 1998; Kohn, Saxena, Levav, & Saraceno, 2004; Wang et al., 2005). For example, in one study, only 40% of those surveyed reported seeking help the same year that their symptoms emerged; among the remainder of this sample, the average length of time that individuals experienced symptoms before seeking help was eight years (Christiana et al., 2000).

**3.2.1 Treatment dropout: consequences and correlates.** In addition to delays in receiving treatment, those who do eventually get help are at high risk for dropping out of treatment despite the very high rates of relapse associated with discontinuing treatment

(Edlund et al., 2002; Melville, Casey, & Kavanagh, 2010; Rossi et al., 2002). Premature dropout has many negative consequences, as truncated treatments are often inadequate. For example, patients who discontinue antidepressant therapy are more likely to relapse (Melfi et al., 1998). Research on psychotherapy suggests that patients optimally improve after 12-13 sessions; however, the average number of sessions attended is often less than five (Hansen, Lambert, & Forman, 2002). Early disengagement from treatment can be especially consequential for individuals who are suffering from severe disorders that require long-term care, such as schizophrenia (Kreyenbuhl, Nossel, & Dixon, 2009). Given the frequency and serious negative consequences of dropout rates, a research literature aimed at elucidating the correlates of early treatment termination has emerged.

Several sociodemographic variables, including sex (i.e., being male), younger age, low socioeconomic status, ethnic status (being from a minority group), and relationship status (being single) are associated with early dropout from treatment (Baekeland & Lundwall, 1975; Edlund et al., 2002; Fischer et al., 2008; Gonzalez, Weersing, Warnick, Scahill, & Woolston, 2011; Kreyenbuhl et al., 2009; O'Brien, Fahmy, & Singh, 2009; Olfson et al., 2009; Rossi et al., 2002). Similarly, certain family characteristics, such as high caregiver stress can increase rates of dropping out of treatment (Baekeland & Lundwall, 1975; Edlund et al., 2002; Pellerin, Costa, Weems, & Dalton, 2010; Rüsch, Todd, Bodenhausen, Weiden, & Corrigan, 2009)). Clinical features, including illness comorbidity, substance abuse, early onset psychosis, and lack of insight into one's illness (Gonzalez et al., 2011; Kreyenbuhl et al., 2009; Lecomte et al., 2008; O'Brien et al., 2009; Olfson et al., 2009; Pellerin et al., 2010). Moreover, particular

attitudes towards treatment (e.g., feeling as though one's treatment is unnecessary, is not meeting one's specific needs, or is not patient-centered), and increased severity of functional impairment or symptomatology have also have also been linked with higher drop-out rates (Gonzalez et al., 2011; Kreyenbuhl et al., 2009; Lecomte et al., 2008; O'Brien et al., 2009; Olfson et al., 2009; Pellerin et al., 2010). Finally, treatment variables can also impact one's probability of discontinuing treatment (Baekeland & Lundwall, 1975; Edlund et al., 2002; Garcia & Weisz, 2002; Lecomte et al., 2008). For example, patients who received a combination of medication and psychotherapy had reduced dropout rates compared to those who received only one of these treatments (Edlund et al., 2002).

**3.2.2 Using patient preferences to mitigate dropout.** Most relevant for the current study, however, is the observation that low levels of patient participation in clinical decision-making are associated with higher dropout rates (O'Brien et al., 2009; Rossi et al., 2002). These findings support the use of shared decision making (SDM) models in which patients' input is solicited regarding which aspects of treatment are of most value to them (Hamann, Leucht, & Kissling, 2003; Karnieli-Miller & Eisikovits, 2009). A cornerstone of the SDM approach is to design healthcare services with patient preferences in mind (Hamann et al., 2003). In this context, a central thesis motivating the current study is that EI services that expressly incorporate the preferences of patients and their family members will better optimize ongoing patient engagement and minimize dropout rates.

The inclusion of patient preferences is a relatively new concept in mental health care (Hamann et al., 2003); however, the benefits are potentially numerous and initial studies suggest promising outcomes (Cunningham, Deal, Rimas, Buchanan, et al., 2008; Cunningham, Deal, Rimas, Campbell, et al., 2008; Dwight-Johnson, Lagomasino, Aisenberg, & Hay, 2004). For example, results from a study examining patient preferences regarding hospital design suggest that many patients would trade moderate wait times over shorter ones in exchange for timely feedback(Cunningham, Deal, Rimas, Campbell, et al., 2008). Other studies have used DCEs to study the treatment preferences of depressed patients (Dwight-Johnson et al., 2004), patient-centered care preferences (Cunningham, Deal, Rimas, Campbell, et al., 2008), or the preferences of parents of children with mental illness regarding information (Cunningham, Deal, Rimas, Buchanan, et al., 2008).

Similarly, we have previously used discrete choice conjoint experimental (DCE) methods to investigate the attributes that patients, family members, and professionals view as important for increasing the likelihood that patients would make initial contact with an EI service (Becker et al., 2014). Respondents fell into two segments based on their preference profile. Both segments would be more likely to contact an EI service that included short wait times, efficient use of appointment times, face-to-face contact, patient autonomy, information regarding psychological treatments, and community education. Respondents in the first segment (44%) placed greater priority on more conventional aspects of mental healthcare such as being treated by psychiatrists/ psychologists and locating the service within a hospital or clinic setting. In contrast, the second segment

(56%) placed greater importance on attributes that made access more convenient, including Internet services, walk-in appointments, and later operating hours. Predicted usage of simulated services also varied across segments. Randomized First Choice (RFC) simulations revealed that the first segment predicted an *E-Health* model would increase rates of contact, while the second segment was somewhat split in their preferences for a *Primary Care* and a *Clinic/ Hospital* model. Additionally, patients and family members' responses differed from those of mental health professionals, emphasizing the importance of seeking patient input. Results from this study identified those EI services attributes that could serve to increase the likelihood that patients and/or their family members would make *initial contact* with the service. However, the results do not identify attributes that may influence patients' *continuing engagement* with an EI mental health service.

**3.2.3 Current study.** Researchers have suggested that patient and family engagement in mental health is comprised of two steps: treatment initiation and ongoing engagement with the service. These two steps are independent of one another and governed by discrete psychological and service factors; thus, each should be studied separately (Westin, Barksdale, & Stephan, 2013). Therefore the current study's aim was to use DCE methods to identify EI service attributes that would increase the likelihood of patients remaining in a treatment once service has been initiated.

Moreover, it is important to consider a variety of perspectives in designing a mental healthcare service. Patients can benefit from being matched to their preferred treatments (Swift, Callahan, & Vollmer, 2011; Swift & Callahan, 2009), while professionals are more likely to adopt research practices that they deem important

(Aarons, 2004). Moreover, patients with mental illness and mental health professionals often have different views of treatment and service priorities (Holley, Hodges, & Jeffers, 1998). In this context, several research questions regarding ongoing engagement in care were posed to patients, their families, and mental health professionals:

*RQ1: Can distinct underlying segments of respondents, based on shared preferences, be identified? What attributes characterize the segments' preferences? Which attributes have the most influence on the segment's preferences?*

*RQ2: Do the segments differ significantly in regards to demographic characteristics or covariates?*

*RQ3: Do the segments differ on how they would prefer EI services to be delivered?*

**3.3 Methods**

The Research Ethics Board at St. Joseph's Healthcare Hamilton approved this study. The methods of this study are similar to the first survey (Becker et al., 2014) and, therefore, will be briefly summarized here.

**3.3.1 Participants.** Participant recruitment occurred in six outpatient clinics affiliated with St. Joseph's Healthcare Hamilton including a mood disorders clinic, an anxiety disorders clinic, a schizophrenia clinic, an early intervention clinic for psychosis, and two general psychiatry clinics. Previous participants (i.e., those who had completed the first survey) and mental health professionals were also recruited via an emailed link. In total, 516 participants completed the computerized survey: 98 patients/ family members from the first survey, 235 new patients/ family members (333 total), and 183

professionals. The respondents ranged in age from 16 to 75+. The age range cannot get anymore specific as it became possible to identify respondents, particularly in the upper age ranges. As such, participants were only asked about which age range they belonged to. Incomplete responders (i.e., those who did not complete all of the conjoint tasks) were eliminated from the analyses. In total, 408 patients and family members were asked to complete the survey, and 333 completed it (81.62% return rate).

**3.3.2 Survey development**. The survey was designed using a conjoint analysis checklist (Bridges et al., 2011) and recommended research practices (F. R. Johnson et al., 2013). Development began with a literature review, which provided a variety of attributes to consider. Candidate attrinutes were further reduced with the aid of four focus groups (three patient groups and one family group). Each group consisted of between five and ten participants, including a moderator and a research assistant. The focus groups followed a moderator's guide with specific questions, were audio taped and transcribed, and each participant received $25.00 for their participation. Clinic staff were asked to be included in three key informant interviews. The most relevant attributes were then framed as 14 4-level statements (see Table 3.1 for the attributes used in this survey). At the beginning of the survey, potentially unfamiliar terms, such as "mental health problems" were defined[1].

**3.3.3 Survey administration.** Sawtooth Software's SSI Web (version 7.0.4) was used to program and administer the survey (*The CBC system for choice-based conjoint*

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[1] "Mental health problems" was defined as: a lot of fear and anxiety, a lot of sadness and depression, hearing voices or seeing things that are not there, and/ or using too much alcohol or drugs.

*analysis*, 2013). The multi-level attributes were presented in a partial profile choice experimental design; that is, respondents were only exposed to a few attributes at a time, rather than all attributes at once (Chrzan, 2010). The experimental design ensured that each respondent was assigned one of the formulated 999 versions of the conjoint survey (*The CBC advanced design module (ADM) Technical Paper*, 2008, *The CBC system for choice-based conjoint analysis*, 2013). In each of the 18 choice tasks, each respondent was asked to choose which service would encourage people to stay in treatment for their mental health problems (see Figure 3.1 for an example of a choice task).

*Welcome to our survey. We want you to help us develop a new mental health service.*

*Click below the service that would most encourage people to stay in mental health treatment.*

| Patients in crisis must wait for their next appointment<br><br>Provides a choice of medication, talk therapies, and diet and exercise as treatments | Patients in crisis can get help during the day on week days<br><br>Only provides talk therapies | Patients in crisis can get help 24 hours per day<br><br>Only provides talk therapies |
| --- | --- | --- |
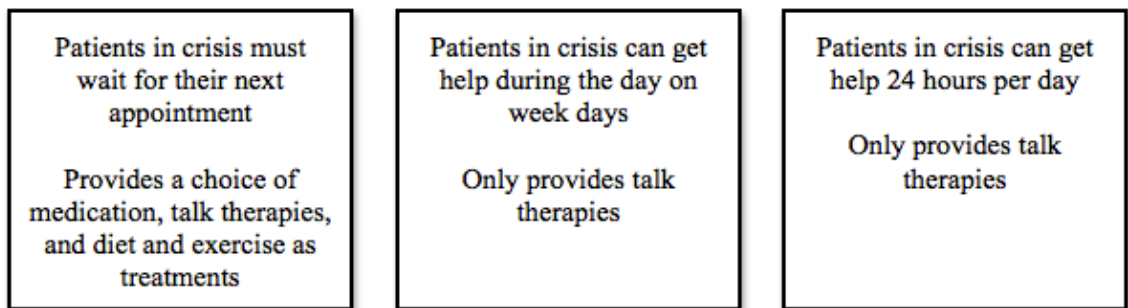
Figure 3.1 Sample conjoint survey choice task. 18 choice tasks were created for each respondent with varied attribute levels. Survey respondents were asked to select which of the three hypothetical EI service options they thought would likely encourage prolonged engagement with a mental health service.

**3.3.4 Other measures.** Demographic information was collected and included: (a) professional background (e.g., mental health professional vs. patient), (b) age, (c) sex, (d) education level, (e) birth country, (f) primary language, (g) years of experience with

mental health services (for patients / family members), and (h) years of professional experience for mental health professionals.

The survey also included a Theory of Planned Behaviour (TPB) scale to gauge people's *intent* to behave in a manner consistent with prolonged EI service engagement (e.g., practicing things they learned between sessions (Ajzen, 1991). TPB predicts that four factors will influence one's intent to behave in a certain way, such as (a) one's *attitudes* towards certain behaviours. For instance, we asked whether people who stay in treatment for mental health problems would stop these problems from getting worse, etc. (b) *Subjective norms* (i.e., a how one perceives a behaviour, which can be influenced by the opinions of others) can also affect one's intent to engage in specific behaviours. (c) *Self efficacy barriers* are factors that may hinder someone's sustained engagement with EI services. We asked whether certain factors would make it hard for someone to stay in treatment for mental health problems, including trusting mental health professionals, etc. Finally, (d) P*erceived behavioural control* was also measured by asking whether it would be easy for someone with a mental health problem to remember to take medications each day at the same time, etc.

**3.4 Procedure**

The procedure for administering the second survey was nearly identical to the previous study (Becker et al., 2014). New patients and family members in clinic waiting rooms were asked to complete a survey. Professionals and patients/ family members who had agreed to be contacted from the first survey were emailed a link to the survey. Written and informed consent was acquired once the study had been fully described to

participants. Following survey completion, participants were given a choice of $15.00 gift cards.

**3.4.1 Statistical analysis.** The survey data was analyzed using Latent Gold Choice 5.0 software, which segmented survey respondents into subgroups characterized by shared preferences (Vermunt & Magidson, 2005). Several information criterion were used to determine how many latent class segments to retain for our dataset, using a maximum likelihood criterion (Lanza & Rhoades, 2013). Latent class models, with one through five solutions were estimated and replicated ten times from random starting numbers. Background (Holley et al., 1998) and intent to use EI services (Ajzen, 1991) were also included as covariates, given that these factors could impact the probability of someone with mental health problems remaining in treatment (Collins & Lanza, 2010).

Utility coefficients and associated Z-scores were computed to determine how desirable the attribute levels were in comparison to one another (see Table 3.1). Any utility coefficient scores associated with a Z-score falling outside of the range of -1.96 to 1.96 are considered to be a statistically significant preference. Attributes with higher importance scores suggest that the attribute levels have a relatively larger range among the utility values; thus, they are more influential on decision-making (Orme, 2010). Importance scores for attributes are calculated using the range of utility values for the attribute levels and are expressed as a percentage of the total range of the level's utility values (Orme, 2010).

RFC simulations were conducted to determine how specific combinations of attributes would be utilized based on the conjoint survey data (*Advanced Simulation*

*Module (ASM) for product optimization v1.5 (Technical paper)*, 2003; Huber, Orme, & Miller, 1999; Orme & Huber, 2000). RFC simulations add variability to utility values, simulate each participant's responses 200,000 times, average these responses, and estimate preference shares. By doing so, RFC simulations reflect real-world decision-making by mimicking the attribute trade-offs that people make (*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*, 2003; Huber et al., 1999; Orme & Huber, 2000).

### 3.5 Results

Participants also completed three hold-out choice tasks (R. Johnson & Orme, 2010). Mean absolute errors (MAE) signify the difference between the actual (observed) responses and a prediction of how people would respond. The average absolute difference between the simulated and observed mean absolute errors (MAE) for the three hold-out tasks were 2.8, 5.14, and 6.24, respectively. While there is no standard or ideal MAE, lower MAE scores are typically more desirable; thus we can conclude acceptable predictive validity.

**3.5.1 RQ1.** Latent Gold Choice 5.0 was used to apply Latent Class Analysis to the conjoint survey data in order to ascertain underlying latent classes or segments among participants (Vermunt & Magidson, 2005). Research has demonstrated that the Bayesian Information Criterion (BIC) yields the best solutions when determining correct number of latent classes to retain (Nylund, Asparouhov, & Muthén, 2007). For the current analysis, BIC yielded a two-class solution, which was straight-forward to conceptualize and label for segmentation purposes (Lanza & Rhoades, 2013).

Zero-centered utility coefficients and z-scores were used to determine which attribute levels were preferred over others (see Table 3.1). Both segments' results indicated that patients would prolong engagement in a service that adopted a collaborative framework with regards to choosing treatment, assigning clinicians based on individual characteristics (e.g., culture, language, and religion), deciding on the level of family involvement, and deciding on how to use peer support (i.e., whether the service is designed by those who have also experienced mental illness). Furthermore, a service that had convenient and fast access to services (including crisis response services that are available 24 hours a day), was located in an office in the community, and had Internet options where people can ask professionals about mental health problems were all indicators of sustained engagement. Services that provided a range of treatment options (i.e., choice of medicine, talk therapies, and diet and exercise as treatments), and addictions services and whose main goal that the service aimed at reducing symptoms including anxiety, depression, and psychosis were also predicted to increase engagement.

Importance scores (see Table 3.2) indicate that the two attributes most likely to influence decision-making were the same for both segments; these attributes were the availability of treatment options for someone who is in crisis (e.g., patients in crisis go to the emergency room, wait for next appointment, can get help during the day on weekdays, and / or get help 24 hours a day) and the option of several different treatment modalities (e.g., medication, talk therapies, diet and exercise, and / or a combination).

Despite the similarities, specific attributes also distinguished the two segments. The first segment (53% of the sample) would be more likely to continue treatment with

an EI service that included: (a) text message and phone help, (b) a mixture of one-on-one sessions with a clinician and group sessions with patients and a clinician, (c) mental health nurse care providers, and (d) appointments on weekday evenings[2]. This segment's importance scores suggest that they are most sensitive to variations in the levels of family involvement and collaborative decision-making. This segment was labeled the *Collaborative* segment.

In contrast, the second segment (47% of the sample) predicted that patients would be more likely to remain in an EI mental health service that included: (a) psychologist or psychiatrist as care providers, (b) phone help, (c) one-on-one sessions with a clinician only, and (d) appointments on weekday afternoons. In terms of importance scores, this segment was most sensitive to variations in professional experience of the care providers (i.e., whether their care was provided by a family doctor, mental health nurse, social worker, or psychologists/ psychiatrist). The second segment was also sensitive to services that emphasize functional outcomes – rather than symptom improvement. These functional outcomes included (a) reducing anxiety, depression, or psychosis, (b) improving relations with partners, family, or friends, (c) helping people function better at school or work, and / or (d) helping people find jobs, housing, or financial help. Given this segment's sensitivity to professional background of the care provider, it was labeled the *Expert* segment.

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[2] Segment preferences are listed in order of most significant to least significant, according to the Z-scores associated with the utility coefficients for each attribute level.

Table 3.1 Zero-centered utility coefficients and Z values for the *Collaborative* and *Expert*

Segments

| Attribute | Collaborative | | Expert | | |
|---|---|---|---|---|---|
| Attribute Levels | U | Z | U | Z | *Wald* |
| **Service Features** | | | | | |
| **Location** | | | | | 115.79*** |
| Is at a patient's home | -0.01 | -0.08 | -0.50 | -4.47 | |
| Is at an office in the community | **0.84** | **8.21** | **0.31** | **3.25** | |
| Is at a family doctor's office | -0.19 | -1.67 | 0.10 | 1.10 | |
| Is at a hospital | -0.64 | -5.38 | 0.08 | 0.86 | |
| **Time of appointments** | | | | | 76.21*** |
| Appointments are on weekday mornings | -0.31 | -2.81 | 0.09 | 0.95 | |
| Appointments are on weekday afternoons | 0.27 | 2.65 | **0.30** | **3.30** | |
| Appointments are on weekday evenings | **0.53** | **5.49** | 0.02 | 0.26 | |
| Appointments are on weekends | -0.49 | -4.30 | -0.42 | -3.90 | |
| **Care from MD, PhD, or RN** | | | | | 260.74*** |
| Care is provided by a family doctor | -0.88 | -6.78 | -0.46 | -3.96 | |
| Care is provided by mental health nurses | **0.61** | **6.07** | 0.10 | 0.96 | |
| Care is provided by social workers | -0.26 | -2.47 | -0.71 | -5.84 | |
| Care is provided by psychologists or psychiatrists | 0.53 | 4.79 | **1.07** | **10.09** | |
| **Treatment Options** | | | | | |
| **Choice of treatment modalities** | | | | | 522.69*** |
| Only provides medication | -1.22 | -7.37 | -0.46 | -4.14 | |
| Only provides talk therapies | -0.12 | -0.92 | -0.47 | -4.08 | |
| Only provides treatments such as diet and exercise | -1.21 | -7.67 | -0.44 | -3.79 | |
| Provides a choice of medication, talk therapies, and diet and exercise as treatments | **2.54** | **17.49** | **1.37** | **12.95** | |
| **Addiction service** | | | | | 263.40*** |
| Does not help with alcohol or drug problems | -1.82 | -9.95 | -0.80 | -6.49 | |
| All patients get help with alcohol or drug problems | **1.14** | **10.14** | **0.45** | **4.53** | |
| The service decides who gets help with alcohol or drug problems | -0.41 | -3.19 | -0.08 | -0.79 | |
| Patients decide if they will get help | 1.10 | 9.69 | 0.43 | 4.52 | |

with alcohol or drug problems

| | | | | | |
|---|---|---|---|---|---|
| **Culture* considered in clinician assignment** | | | | | 124.97[***] |
| Culture* is not considered when assigning clinicians | -1.35 | -8.66 | -0.03 | -0.27 | |
| The service decides if culture[3] is considered when assigning clinicians | -0.26 | -2.13 | 0.05 | 0.56 | |
| Patients decide if culture* is considered when assigning clinicians | **0.85** | **8.01** | **0.24** | **2.66** | |
| Culture* is always considered when assigning clinicians | 0.76 | 7.05 | -0.27 | -2.61 | |
| **Individual vs. Group treatment** | | | | | 90.97[***] |
| All sessions are alone with a clinician | 0.01 | 0.12 | **0.37** | **3.94** | |
| Most sessions alone with clinician, some with a small group of patients and a clinician | **0.60** | **6.16** | 0.12 | 1.26 | |
| Some sessions alone with a clinician, most with a small group of patients and a clinician | 0.27 | 2.68 | -0.33 | -3.21 | |
| All sessions are with a small group of patients and a clinician | -0.88 | -7.11 | -0.16 | -1.63 | |
| **Emphasized outcomes beyond symptoms** | | | | | 262.42[***] |
| Main goal is to reduce anxiety, depression, or psychosis | **1.03** | **10.30** | **0.91** | **9.43** | |
| Main goal is to improve relations with partners, family, or friends | -0.34 | -3.03 | -0.13 | -1.22 | |
| Main goal is to help people function better at school or work | -0.23 | -2.21 | -0.22 | -2.21 | |
| Main goal is to help people find jobs, housing, or financial help | -0.46 | -4.10 | -0.56 | -4.98 | |
| **Service Supports Provided** | | | | | |
| **Crisis response** | | | | | 371.79[***] |
| Patients in crisis must go to an emergency room for help | -0.29 | -2.05 | -0.20 | -1.84 | |
| Patients in crisis must wait for their next appointment | -2.29 | -8.72 | -1.01 | -7.80 | |
| Patients in crisis can get help during the day on week days | 0.26 | 1.97 | 0.22 | 2.29 | |
| Patients in crisis can get help 24 hours per day | **2.32** | **14.62** | **0.98** | **10.32** | |
| **Internet options** | | | | | 158.98[***] |

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[3] culture, language, and religion.

| | | | | |
|---|---|---|---|---|
| No internet options | -1.53 | -9.67 | -0.43 | -4.02 | |
| Has a professionally supervised internet site where patients talk to each other | 0.02 | 0.20 | -0.07 | -0.73 | |
| Has an internet site where patients ask professionals about mental health problems | **0.79** | **7.55** | **0.26** | **2.72** | |
| Has an internet site were patient can learn skills to manage mental health problems | 0.72 | 7.24 | 0.24 | 2.69 | |
| **Text message & phone support** | | | | | 203.52*** |
| No text messages or phone help | -1.48 | -9.01 | -0.51 | -4.62 | |
| Includes helpful text messages | 0.12 | 1.11 | -0.33 | -3.22 | |
| Includes phone help | 0.49 | 4.91 | **0.57** | **6.48** | |
| Includes helpful text messages and phone help | **0.87** | **8.60** | 0.27 | 2.88 | |
| **Patient Choice / Input** | | | | | |
| **Family involvement** | | | | | 319.58*** |
| Families are not involved | -1.89 | -9.31 | -0.71 | -6.28 | |
| Clinicians decide whether families are involved | -0.97 | -6.04 | -0.22 | -2.23 | |
| Patients decide whether families are involved | 1.06 | 9.21 | 0.31 | 3.25 | |
| Clinicians and patients decide together whether families are involved | **1.80** | **14.67** | **0.62** | **6.69** | |
| **Peer support** | | | | | 154.06*** |
| People who have experienced mental health problems do not help design or provide this service | -1.34 | -8.30 | -0.29 | -2.77 | |
| People who have experienced mental health problems helped design this service | **0.84** | **8.03** | **0.38** | **4.11** | |
| People who have experienced mental health problems help provide this service | 0.57 | 5.53 | 0.21 | 2.28 | |
| People who have experienced mental health problems provide this service | -0.07 | -0.68 | -0.31 | -3.08 | |
| **Collaborative decision making** | | | | | 144.43*** |
| Clinicians choose the treatment | -1.70 | -9.32 | -0.31 | -2.85 | |
| Patients are told about treatment options but make their own choice | 0.24 | 2.13 | -0.17 | -1.71 | |
| Clinicians recommend treatments but patients make the final choice | 0.47 | 4.53 | 0.09 | 0.87 | |
| Patients and clinicians together choose the treatment | **0.99** | **9.00** | **0.39** | **4.34** | |

*Note.* U = Utility coefficients. The higher the value, the stronger one's prediction that that particular attribute level will encourage one to remain engaged in EI services (Orme, 2010).

Z = Z scores. If a Z-score associated with a utility coefficient is outside of the range of -1.96 to 1.96, that utility coefficient value can be considered significant (i.e., significantly preferred).

The highest U and Z values within each segment are in bold.

***p<0.001.

Table 3.2 Standardized importance scores for the *Collaborative* and *Expert* Segments

|  | Latent Class Segment | | | |
|  | *Collaborative* | | *Expert* | |
| EI Service Attributes | R | I | R | I |
| **Service Features** |  |  |  |  |
| Care from MD, PhD, or RN | 10 | 4.43 | 3 | 11.38 |
| Location | 12 | 4.39 | 8 | 5.22 |
| Time of appointments | 14 | 3.03 | 9 | 4.63 |
| **Treatment Options** |  |  |  |  |
| Choice of treatment modalities | 2 | 11.15 | 2 | 11.84 |
| Addiction service | 4 | 8.78 | 6 | 7.99 |
| Culture considered in clinician assignment | 8 | 6.52 | 14 | 3.27 |
| Emphasized outcomes beyond symptoms | 11 | 4.42 | 4 | 9.46 |
| Individual vs. Group treatment | 13 | 4.37 | 10 | 4.51 |
| **Service Supports Provided** |  |  |  |  |
| Crisis response | 1 | 13.69 | 1 | 12.79 |
| Text message & phone support | 6 | 6.96 | 7 | 6.93 |
| Internet options | 7 | 6.88 | 11/12 | 4.49 |
| **Patient Choice / Input** |  |  |  |  |
| Family involvement | 3 | 10.93 | 5 | 8.56 |
| Collaborative decision making | 5 | 7.97 | 11/12 | 4.49 |
| Peer support | 9 | 6.48 | 13 | 4.43 |

*Note.* R = the attributes have been ranked from 1 to 14, 1 being the most important. I = Importance scores, expressed as percentages. An attribute with a higher importance score is considered more influential in decision-making (Orme, 2010).

**3.5.2 RQ2.** Demographic analyses (Table 3.3) reveal that there were significant differences between segments in professional background, sex, and education. . Specifically, 58% of the *Collaborative* segment was comprised of professionals, whereas 88% of the *Expert* segment was made up of patients and family members. The entire

survey sample was comprised mainly of women (73.1%); however, the majority of the

females in this sample were members of the *Collaborative* segment (60.2%).

Table 3.3 Demographics of the *Collaborative* and *Expert* latent class segments

| | N | % | Latent Class Segment | | $\chi^2$ |
| --- | --- | --- | --- | --- | --- |
| | | | *Collaborative* | *Expert* | |
| Sample Size | 516 | 100 | 53.1 | 46.9 | |
| Background | | | | | 120.6*** |
| Patient/ Family members | 333 | 64.5 | 36.1 | 63.9 | |
| Professional | 183 | 35.5 | 86.3 | 13.7 | |
| Age | | | | | 5.7 |
| 16-20 | 21 | 4.0 | 42.9 | 57.1 | |
| 21-35 | 137 | 26.6 | 51.1 | 48.9 | |
| 36-55 | 280 | 54.3 | 52.9 | 47.1 | |
| 55+ | 78 | 15.1 | 65.4 | 34.6 | |
| Sex | | | | | 25.0*** |
| Male | 135 | 26.2 | 35.6 | 64.4 | |
| Female | 377 | 73.1 | 60.2 | 39.8 | |
| Transgender | 4 | 0.8 | 75.0 | 25.0 | |
| Education | | | | | 29.1*** |
| High school or less | 87 | 16.9 | 27.6 | 72.4 | |
| High school or higher | 429 | 83.1 | 59.2 | 40.8 | |
| Birth country | | | | | 0.1 |
| Born in Canada | 441 | 85.0 | 54.2 | 45.8 | |
| Born in another country | 75 | 15.0 | 52.0 | 48.0 | |
| Language | | | | | 4.5 |
| English | 458 | 88.8 | 53.3 | 46.7 | |
| French | 12 | 2.3 | 33.3 | 66.7 | |
| Other | 46 | 8.9 | 65.2 | 34.8 | |
| Years Experience | | | | | 7.7 |
| Not using services | 58 | 17.5 | 44.8 | 55.2 | |
| Less than 1 year to 4 years | 158 | 47.4 | 32.3 | 67.7 | |
| 5 to more than 10 years | 117 | 35.1 | 36.8 | 63.2 | |
| Professional Experience | | | | | 1.96 |
| Less than 1 year to 10 years | 71 | 38.8 | 84.5 | 15.5 | |
| 11 to 20 years | 44 | 24.0 | 84.1 | 15.9 | |
| 21 to more than 25 years | 68 | 37.2 | 89.8 | 10.2 | |

***p<0.001.

Covariate parameter estimates (U) were also computed to determine the strength

of the relationship between two covariates (professional background and intent) and

membership in a particular segment. In this regard, membership in the *Expert* segment

was associated with being a patient or family member (U= 0.47, Z= 6.24, p<0.001) and

with behaviours associated with higher intent to remain engaged in EI services than the

*Collaborative* segment (U= 0.05, Z= 3.66, p<0.001). There was also a significant

difference between the segments in regards to education (the *Collaborative* segment had

higher levels of education than the *Expert* segment), though this is highly correlated with

background and, therefore, will not be discussed further.

**3.5.3 RQ3.** This study sought to determine which service attributes would

increase the likelihood of patients staying engaged in treatment. In addition, we wanted to

know which hypothetical service models patients would be most likely to utilize in an

ongoing, long-term manner. Using each respondent's individual[4] utility coefficients from

the conjoint survey, RFC simulations predicted how much utilization each service model

would receive.

Three EI services models were designed: (1) An *E-health* service characterized by

the following attributes: (a) being used at the patient's home, (b) text messaging and

phone help provided, (c) talk therapies available, (d) care provided by mental health

nurses, and (e) an internet site where patients can learn skills to manage mental health

problems. (2) A *Community* service characterized by: (a) being located at an office in the

community, (b) no text messages or phone help, (c) choice of medication, talk therapies,

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[4] *Note*. While the coefficients used for RFC simulations were individual, the rest of the data analysis was based on aggregate utility scores.

and diet and exercise as treatments, (d) care provided by mental health nurses, and (e) no

internet options. (3) A *Hospital* service characterized by: (a) being located at a hospital,

(b) no text messages or phone help, (c) choice of medication, talk therapies, and diet and

exercise as treatments, (d) care is provided by psychologists or psychiatrists, and (e) no

internet options. The results from the RFC simulations (see Table 3.4) showed that 69%

of the *Collaborative* segment thought patients would be most likely to use an *E-Health*

service while 60% of the *Expert* segment thought patients would be most likely to

maintain their involvement with a *Hospital* service.

Table 3.4 Randomized First Choice (RFC) simulations for the *Collaborative* and *Expert*

latent class segments

| | | | Latent Class Segment | | | |
| | Total | | *Collaborative* | | *Expert* | |
| | % | SE | % | SE | % | SE |
|---|---|---|---|---|---|---|
| **EI Service Simulation** | | | | | | |
| E-Health | **44.53** | **1.23** | **69.38** | **0.47** | 15.49 | 0.49 |
| Community | 25.33 | 0.20 | 25.99 | 0.26 | 24.56 | 0.31 |
| Hospital | 30.14 | 1.27 | 4.62 | 0.24 | **59.95** | **0.77** |

*Note.* RFC simulations are used to predict the utilization of a particular model made up of a specific combination of attribute levels (*Advanced Simulation Module (ASM) for product optimization v1.5 (Technical paper)*, 2003; Huber, Orme, & Miller, 1999; Orme & Huber, 2000).
*%* = Percentage of participants that would hypothetically prefer or utilize a service made up of specific attribute levels.
*SE* = Standard error (U/Z).

## 3.6 Discussion

This study used DCE methods to ascertain which EI service attributes would be

most likely to encourage patients to remain in mental health treatment for a prolonged

period of time, according to patients, their family members, and mental health professionals.

**3.6.1 Summary of results.** The LCA analysis identified two segments. Both segments estimated that people with mental health issues would be more likely to remain in an EI mental health service that reflected a collaborative framework. For instance, both preferred to be included in decisions involving choosing a treatment, assigning clinicians based on culture, and decisions involving level of family involvement and peer support. Moreover, both segments indicated that fast access to a service would encourage long-term engagement with treatment. For example, crisis response available 24 hours a day, a service located in an office in the community, and Internet options where people can ask professionals about mental health problems. Services that provided a range of treatment options, provided addiction services, and aimed to reduce psychiatric symptoms were also predicted to increase patient engagement in the long term. Both segments rated the same attributes as being most influential in decision-making (i.e., crisis response and numerous treatment options).

There were also some differences between the segments. The *Collaborative* segment predicted that text message and phone help and a mixture of private sessions with a clinician and group sessions with other patients would increase sustained engagement in EI services. The *Collaborative* segment was more sensitive to the attribute levels for family involvement and collaborative decision-making. Conversely, the *Expert* segment predicted that EI services that included psychologists and/or psychiatrists as care

providers and phone help would increase engagement. They were sensitive to variations in professional background and treatment outcomes.

Membership in the *Collaborative* segment was associated with being a professional and also with lower TPB scores measuring intent to engage in a specific behaviour (in this case, the behaviour is remaining in treatment for an extended period of time). Membership in the *Expert* segment was associated with being a patient or family member and with higher intent. Both segments had a high volume of females, though S1 had the majority of female respondents (60.2%).

The RFC simulations demonstrated that the majority (69%) of the *Collaborative* segment predicted that people with mental health problems would remain engaged in treatment over a sustained period of time if an *E-Health* model were available. In contrast, the *Expert* segment predicted that patients would remain engaged with EI services in a *Hospital* model. Professionals predicted that patients would likely remain engaged with an *E-Health* service model while many patients thought individuals with mental health problems would be more likely to remain engaged with a *Hospital* model.

## 3.7 Implications

**3.7.1 Approaches for increasing service contact and engagement.** The similarities between the segments are in contrast to our previous findings, which indicated that a range of different options would be most beneficial to the to identified segments in order to increase the likelihood that they would make initial contact with a service (Becker et al., 2014). In contrast, the results of this survey suggest that the attributes that encourage long-term utilization of services are much more similar across

segments. This suggests that clinics may not need not to tailor the attributes of their service to meet the needs of distinct groups of patients to the same extent when focusing on providing services that will keep patients engaged over the long term as compared to when they are focused on encouraging initial contact. This study revealed key attributes (namely the availability of crisis response services and a range of treatment options) that are critical for ongoing engagement regardless of segment. Therefore, including these attributes in the design of EI services will likely encourage ongoing service engagement across most patients and their families.

**3.7.2 Expedient access to mental health services.** Continuously available crisis response emerged as the most important variable when encouraging ongoing engagement with EI services. As such, expedited access to crisis healthcare should be a top priority. This is similar to our first survey's findings, which underscored the importance of reduced wait times for most respondents, highlighting the need for engaging those with mental illness in ways that are efficient and rapid.

**3.7.3 E-health.** E-health methods may be a viable way to facilitate access to future EI services. Attributes related to e-health, such as phone and text message help and Internet websites where people can get assistance, were estimated to encourage sustained engagement with EI services. Moreover, the RFC simulations from both surveys suggest that many people would utilize e-health modes of service delivery over more traditional ones (e.g., face-to-face). This has been investigated by Kenter et al. (2013) who examined the rates of people who used an Internet service while waiting for face-to-face treatment as well as the number of resulting drop-outs. About half of the

patients utilized the Internet option rather than waiting for face-to-face treatment. Despite the high number of those who began online treatments, 65% completed 3 or more sessions, while only 18% finished treatment completely; however, those who received online treatment clinically improved to a greater degree than those who did not (Kenter, Warmerdam, Brouwer-Dudokdewit, Cuijpers, & van Straten, 2013). These results suggest that online treatments are feasible and often desirable but may not be sufficient to ultimately sustain the level of engagement necessary to optimize treatment outcomes and benefit.

**3.7.4 Collaborative healthcare.** Similar to the first survey (Becker et al., 2014), and consistent with our expectation, the preferences of patients and family members differed from the perceived preferences of patients by mental health professionals. Other researchers (Holley, Hodges, & Jeffers, 1998) have found that the preferences of mentally ill patients often differ from those expressed by professionals or family members. This study went one step further by asking professionals to suppose what attributes of a mental health service would motivate patients to remain involved in EI services over a prolonged period of time. The similarities between the two segments suggest that professionals partly understand what attributes will encourage patient engagement. For instance, they correctly estimated that patients would prefer shorter wait times and more choice regarding treatment options. However, professionals seemed to overestimate patient's desire for novel service attributes (e.g., internet access, community settings, allied health professionals) and underestimate other conventionally valued attributes (i.e., clinics staffed by psychiatrists and psychologists and located in

hospital settings). These data suggest that the actual attribute preferences of patients vary from clinical characteristics that professionals believe are important to patients. As such, incorporating patient preferences and values is essential and should be included alongside professional expertise when designing and implementing EI services will provide added value.

**3.7.5 Patient choice/ individually tailored treatments.** Research suggests that one of the reasons for increased dropouts is the lack of a patient-centered model of healthcare (O'Brien, Fahmy, & Singh, 2009; Rossi et al., 2002). Importance scores suggest that services providing a range of treatment options will be helpful in engaging people in treatment; however, respondents differed in the amount of collaborative decision-making they prefer. Despite the many benefits of SDM (Hamann, Leucht, & Kissling, 2003; Karnieli-Miller & Eisikovits, 2009), there were some respondents that preferred a service with a more conventional decision-making structure (i.e., with more responsibility for treatment decisions in the hands of healthcare providers) (Hamann et al., 2003; Karnieli-Miller & Eisikovits, 2009). As such, services that determine how patients would like to approach the decision-making process should maximize service utilization.

The results of this survey and the previous survey (Becker et al., 2014) suggest that professional background of clinical staff is consistently influential in at least one segment's decision-making. In this regard, it is important to offer a range of services staffed with various healthcare providers. Moreover, the differences between the segments in regards to gender should be taken into consideration. Both surveys support

the idea that men and women may experience mental illness differently and should,

therefore, have treatments available that reflect these differences (Afifi, 2007).

**3.8 Limitations**

Several limitations inherent within this study should be considered when

interpreting these results. First, the survey asked respondents to pick the option that

would most encourage people to stay in mental health treatment. Many of the participants

completing this survey were recruited from participation in the last survey or local,

hospital-based clinics. As such, they are likely more accepting of traditional healthcare

models and the study's population may not be completely representative of all those who

would seek continued care for mental illness. Therefore, this study should be replicated

with different populations recruited from different treatment settings. Despite this

limitation, using participants that are experienced mental health service users is also

advantageous. They may have a unique perspective as they are already involved in

services, and can effectively comment on which service attributes are most important or

should be prioritized. Nonetheless, future exploration should investigate attributes that

may reduce attrition and encourage someone to stay in treatment for those in need of, but

not yet involved with, treatment services. Second, the conjoint results would differ if

there had been more attributes included in the survey (Armitage & Conner, 2001). Third,

RFC simulations assess the likelihood that a service comprised of certain attributes will

be utilized. However, this does not account for cost, real-world feasibility, or other

mitigating factors that could make such a service potentially impossible.

**3.9 Conclusions**

The service attributes estimated to reduce attrition and encourage long-term participation in treatment differed from those identified to ensure initial contact with a service. The attributes most likely to encourage sustained engagement with a mental health service included providing a range of treatment modalities and effective crisis response. The importance of these attributes was shared across the two identified segments in the study sample. Therefore, while a range of service options may be essential to increase initial contact, a more homogenous service design may be sufficient to promote continued engagement.

**CHAPTER 4**

**GENERAL DISCUSSION**

**Chapter 4**

This chapter will attempt to frame the studies outlined in Chapters 2 & 3 within a broader context and highlight major policy and clinical implications. This chapter will begin with a summary of the purpose of the research project and study findings. Significant implications of this research, limitations, future directions, and conclusions will follow.

**4.1 Summary of thesis**

**4.1.1 Purpose of the thesis project**. The objective of this thesis was to examine patient-preferred EI service attributes that would increase service user initiation, utilization, and engagement. Using a DCE framework, two surveys were administered. The first survey (Chapter 2) specifically aimed to identify attributes that would maximize the likelihood that someone with emerging symptoms would initiate contact with a service. The second study (Chapter 3) asked which EI service attributes would increase the chances that a patient would continually engage in mental health services over time. Below is a summary of the survey results.

**4.1.2 Survey 1.** The first survey identified two latent subgroups, a *Conventional Service* segment and a *Convenient Service* segment. Both segments estimated that patients would be more likely to contact an EI service that was comprised of specific characteristics. These included a service that allowed for minimal wait times and time demand, increased patient choice, involvement of a variety of mental health professionals, access to information regarding psychological treatments, a community education component, and was endorsed by those who had also used the service.

The *Conventional Service* segment (44% of the sample) predicted that people would contact an EI service comprised of attributes consistent with more traditional healthcare models. For example, a service located at a clinic or hospital and a service staffed by psychologists and psychiatrists. This segment was especially sensitive to variations in levels of background (e.g., patients would likely prefer to interact with someone who had experienced mental illness vs. a physician). Membership in the *Conventional Service* was associated with being a patient or family member and was also associated with being male. RFC simulations determined that this segment predicted that patients would be likely to use either a *Clinic/ Hospital* model (e.g., located at a clinic or a hospital, family doctor or mental health professional referral, etc.) or a *Primary Car*e model (e.g., service at a family doctor's office, self-referral, etc.).

The *Convenient Service* segment (56% of the sample population) predicted that people would be more likely to contact an EI service that was easy to use and access. For example, a service where people can refer themselves, a service that can be used from one's home, a service that is open to walk-in appointments, etc. This segment was sensitive to variations in wait times (e.g., this service starts immediately vs. people wait for six months for this service to start). The *Convenient Service* segment was associated with being a professional and female. Moreover, RFC simulations revealed that this group estimated patients would be more likely to utilize an *E-Health* model. This type of service model would include service contact at an Internet site, being used from one's home, and self-referral.

**4.1.3 Survey 2.** The second survey's aim was to determine which EI attributes would maximize the likelihood of someone remaining involved with mental health services over the long term. Once again, LCA identified two segments, a *Collaborative* segment and an *Expert* segment. Both segments estimated that patients would be more likely to stay in treatment if the service consisted of specific characteristics. These characteristics included an SDM model (e.g., clinicians and patients decide together whether families are involved), convenient and fast access (e.g., patients in crisis can get help 24 hours per day), a range of treatment options (including addiction services), and a service whose main goal was to reduce psychiatric symptoms. Both segments were most sensitive to variations in the levels of crisis response, and both preferred a service that provided help 24 hours a day for patients in crisis. Moreover, the second most important attribute for both segments was treatment options, with both preferring that a service provide a choice of medication, talk therapies, and diet and exercise as treatments.

The *Collaborative* segment (53% of the sample) predicted that patients would be more likely to remain engaged in a service that included text messaging and phone help, mental health nurses as care providers, weekday evening appointments, and one-on-one sessions with a clinician as well as those with small groups. This segment was sensitive to variations in family involvement, preferring that clinicians and patients decide together on the level of family involvement. This segment was also sensitive to the collaborative decision-making attribute, and preferred an SDM model of care when deciding on treatment. Membership in this segment was associated with being a professional and female. RFC simulations indicated that respondents predicted that patients would be more

likely to remain engaged in an *E-Health* EI service model. This service model included: being used from home, text messaging and phone help, and an Internet site where patients can learn skills to manage mental health problems. This segment was also associated with a higher intent to use EI services.

The *Expert* segment (47% of the sample) predicted that patients would be likely to remain engaged in treatment that was comprised of these attributes: weekday afternoon appointments, one-on-one sessions with a clinician only, phone help only, and a psychologist or psychiatrist as the care provider. This segment was sensitive to variations in professional background, and preferred that psychologists or psychiatrists provided care. This segment was also sensitive to the outcome of treatment, preferring a service whose main goal was to reduce anxiety, depression, or psychosis. Segment membership was associated with being a patient or family member and male. According to RFC simulations, this segment estimated that people would be more likely to remain in an EI service that was delivered via a *Hospital* model. This service model included a hospital location, psychologists and psychiatrists as care providers, no text or phone help, etc.

**4.2 Implications for the design of EI mental health services**

**4.2.1 Developing a collaborative or SDM model of healthcare.** In the first study, both segments suggested that attributes enhancing autonomy (e.g., being able to decide on the level of family involvement) would increase rates of initiation with EI services. Similarly, the second survey highlighted the fact that at least half of the survey respondents preferred a more collaborative approach. These results underscore the importance of healthcare models that incorporate patient choice and autonomy. Not only

will this allow people to tailor their treatment to their individual needs and priorities, it should increase their satisfaction with and engagement in treatment. In turn, within an SDM model, patients preferring a more conventional approach to treatment and decision-making will also be able to express and affect this desire.

These results are consistent with other research investigating patient roles and responsibilities. In general, mental health patients often desire more of an active role in their treatment (Adams, Drake, & Wolford, 2007; Murray, Pollack, White, & Lo, 2007). Even those with severe mental illnesses prefer an SDM model, particularly around decisions regarding medications (Adams et al., 2007). An SDM model is linked with increased treatment contact and patient empowerment (Street, Makoul, Arora, & Epstein, 2009). In a systematic review of RCTs, SDM interventions were compared to non-SDM interventions (Joosten et al., 2008). Eleven studies were included, two of which looked at SDM in mental healthcare, while the rest were a combination of various healthcare fields. Overall, the studies revealed increased satisfaction and adherence in the context of SDM, but this is specific to treatments that were more than one session in length. Moreover, according to the authors, when people with chronic illnesses are able to be involved in their treatment decisions, they are more likely to adhere to those treatments. An implication of these findings is that SDM should be considered a process, rather than single events (Joosten et al., 2008).

**4.2.2 Professional's opinions vs. what patients really want.** Importantly, in both surveys, patients and professionals differed in their responses to choice scenarios and, therefore, their attribute priorities. Professionals were asked to hypothesize which

service attributes would impel patients to make contact and remain engaged with EI services. Although their responses were sometimes in line with patient preferences, they were also consistently at odds with those of the patients. For example, in both surveys, the segmentation by LCA revealed that the majority of patients and family members belonged to a different segment than professionals.

Other researchers have found similar results, in that the preferences of patients and professionals in mental healthcare often differ (Holley, Hodges, & Jeffers, 1998). For example, Holley et al. (1998) interviewed 183 patients being considered for relocation, as well as family members of 130 patients and found that the preferences or perspectives of patients differed from those of their family members (Holley et al., 1998). For instance, 41% of patient-family pairs disagreed about the desirability of being relocated from a psychiatric facility to community care, 49% disagreed on the proximity of patient to family, and 53% disagreed on the support provided by the family after relocation. Moreover, 49% of patients preferred to live independently; however, a significantly smaller percentage of family members (10%) and professionals (17%) preferred this. Patients were also in disagreement with family members and care providers regarding employability (Holley et al., 1998). Furthermore, in a two-phase study, researchers surveyed doctors to have them rate information categories in order of importance regarding what to tell a patient regarding medication (Berry, Michas, Gillie, & Forster, 1997). They then surveyed a sample of people with four explanations a doctor may give when prescribing medication, and asked respondents which explanation they preferred.

People's preferred explanations were in contrast to what doctors had indicated would be important for patients to know (Berry et al., 1997).

As such, a collaborative healthcare model that is designed with a variety of perspectives in mind may be most beneficial. In this vein, the mental health field is moving away from paternalistic models to collaborative models (Charles, Whelan, & Gafni, 1999). Combining professionals' expertise with the preferences of the patients and their family members could result in more effective treatment services that reflect the actual needs of the service users.

The preferences surrounding aspects of professional background of the service providers were influential in both surveys. This is consistent with another study conducted on patient preferences regarding various aspects of professionals (McGuire-Snieckus, McCabe, & Priebe, 2003). In a 2003 study, the preferences of 133 mental health patients were solicited regarding how they prefer to be addressed (e.g., patient, client, or service user), how they prefer to address professionals (e.g., by first or last name), how patients would like to be addressed by specific professionals, and their preferences in whether the professional was dressed formally or casually (McGuire-Snieckus et al., 2003). Overall, 75% of respondents preferred to be addressed as 'patients' by general practitioners and 67% preferred to be addressed as such by psychiatrists (McGuire-Snieckus et al., 2003). In terms of being addressed by professionals, 71% of patients preferred that general practitioners call them by their first name, and 68% wished the same of psychiatrists. Moreover, many participants expressed a preference for addressing general practitioners (81% of respondents) and psychiatrists

(80%) by their title and last names. A slightly smaller percentage of participants preferred that general practitioners and psychiatrists be formally attired (67% and 66%, respectively) (McGuire-Snieckus et al., 2003).

While incorporating patient preferences is clearly important, it can be problematic as well. After conducting literature reviews and informal interviews with doctors of a variety of specializations, Say & Thomson (2003) revealed some interesting issues that may arise when doctors try to involve patients in decisions involving their healthcare. Doctors often perceived that there was not enough time to involve patients, and worried that they did not have the right set of communication skills to adequately involve patients, particularly if they felt they did not know the patient well enough. Furthermore, some doctors felt a resistance from their patients when asked about their preferences or a lack of understanding in the information they were provided (Say & Thomson, 2003). Conjoint analysis and DCEs are useful in determining the true preferences of patients, allowing doctors to provide the most salient information possible.

**4.2.3 A range of service options will maximize utilization.** The overall findings of both surveys suggest that a single model or solution is unlikely to suit everyone. The fact that there are distinct latent classes within both datasets suggests that there are subgroups in mental health populations that have divergent treatment priorities and service preferences. Offering a variety of services is especially important when encouraging people to initiate contact with mental health services and attend their first appointment; however, it may not be as imperative to offer as wide an array of services when encouraging people to remain engaged in treatment. Specifically, both segments in

the second study were highly sensitive to the availability of crisis response and treatment options, suggesting that these should be priorities for EI services.

Sex should also be an important consideration when designing mental health services. In both surveys, the respondents' sex played a role in the segmentation analysis. Interestingly, the female responses matched more closely with those of professionals, and the males in both surveys matched with those of patients and family members. There could be several reasons for this: (1) Many of the respondents who filled out the first survey also agreed to fill out the second one; thus, it could be an effect particular to this sample. Replication with a newly recruited sample is necessary to determine this. (2) The sex differences may have arisen as a product of recruitment bias. That is, women are often juggling many roles at one time (e.g., mother, caregiver, employee, spouse, kin keeper, etc.), which may explain why women were much more inclined to want convenient and accessible services. (3) Professionals recommended offering services that are more convenient (i.e., e-health) perhaps as a result of their experience with more traditional services which can often be less convenient to access. (4) There is also the possibility that female patients and professionals are more attuned to novel aspects of care and perhaps favor less conventional styles of service delivery.

Offering a range of services based on sex is consistent with research that suggests that men and women experience mental health differently (Afifi, 2007). Afifi (2007) states that individual risks to developing a mental disorder are often sex-specific; thus, the services that treat the same disorders should be sex-specific, as well. Moreover, the author states that sex may play a role in health-seeking behaviors (Afifi, 2007). As such,

providing EI services that are tailored to the individual needs of men and women may increase uptake and engagement, as well.

In one study, researchers aimed to identify sex differences in psychopathology, treatment, and outcomes for people with major depressive disorder (MDD) (Schuch, Roest, Nolen, Penninx, & de Jonge, 2014). Women were found to have earlier age of onset, higher risk of comorbidity with panic disorder and agoraphobia, and a lifetime diagnosis of an anxiety disorder. Moreover, men were more likely to have contact with mental healthcare providers and substance abuse services, while women were more likely to contact an alternative care provider. The authors conclude by stating that, given men's high comorbidity (48%) of MDD and substance abuse, there should be efforts made to educate them on these topics. Meanwhile, their results determined that women are more likely to develop metabolic syndromes, which can place them at risk for cardiovascular diseases. This should be taken into account when women are given specific medications for MDD (Schuch et al., 2014). In tailoring certain interventions to address sex differences such as these, outcomes will likely improve.

**4.2.4 The need for rapid access to mental healthcare services**. In both studies, there was an emphasis placed upon rapid access to mental health services. In the first study, the *Convenient Service* segment was especially sensitive to wait times. Moreover, in the second study, both segments had high importance scores for crisis response, preferring a service they could access 24 hours a day. A more easily accessible healthcare model (such as e-health models) may increase service contact, utilization and engagement. Moreover, less wait times could encourage people to get help when they

first experience emerging symptoms, lessening the negative impact of untreated mental illness.

Research suggests that timely access to services is vital for the treatment of people with serious mental illnesses. Increased time spent waiting for a psychiatric appointment is associated with more hospitalizations and a risk for suicide (Williams, Latta, & Conversano, 2008). Moreover, when wait times dropped from 13 days to zero days, the rate of people who did not show up for their appointments dropped by 34% (Williams et al., 2008). Longer wait times are also associated with lower rates of adherence and kept appointments (Gallucci, Swartz, & Hackerman, 2005). One study examined 5,901 consecutive patients in a community psychiatry clinic and their failure to keep initial appointments (Gallucci et al., 2005). Overall, 31% of patients cancelled or did not show up to their scheduled appointment. Interestingly, the number of patients who did not show up increased as the delay between initial contact and first appointment increased. For instance, 12% of people did not show up to an appointment made on the same day as initial contact, 23% for appointments scheduled the day after initial contact, 42% for delays of up to a week, and 44% for a delay of 13 days. The authors concluded that, since the rates of people not showing up seemed to stabilize after a week, interventions that take place after one week may not be effective for ensuring patient engagement (Gallucci et al., 2005). As such, minimizing the time patients must wait for an appointment may increase engagement with EI services.

One way of accomplishing this could be with an e-health model. The RFC simulation results for both studies suggest that about half of each study population would

prefer an e-health model, while the other half would prefer a more traditional healthcare service. E-health treatments (i.e., telemedicine, email, phone, etc.) are becoming more popular for areas that are secluded (i.e., rural) (Hilty et al., 2006). A comprehensive review was conducted on the telepsychiatry literature in 2004, focusing mainly on videoconferencing and how it compared to face-to-face services (Hilty, Marks, Urness, Yellowlees, & Nesbitt, 2004). The authors concluded that telepsychiatry is a feasible form of healthcare that increases access, improves outcomes, and satisfies both patients and providers (Hilty et al., 2004).

   **4.2.5 Design and methods of DCEs.** Both studies used a DCE to obtain a variety of perspectives on the design of an EI mental health service. DCEs have many advantages (outlined in Chapter 1), and effectively elicited preferences for patients, their family members, and professionals in the two DCEs conducted. Furthermore, conjoint methods can also effectively elicit preferences for those with serious mental disorders (Bridges, Kinter, Schmeding, Rudolph, & Muhlbacher, 2011). DCEs are a valid and robust method for conducting research on preferences (Orme, 2010; Phillips, Johnson, & Maddala, 2002) and can reveal and eliminate hidden biases (Caruso, Rahnev, & Banaji, 2009; Phillips et al., 2002). The statistical analyses that can be performed on conjoint data are powerful and informative, providing an in-depth look at the study population (Lanza & Rhoades, 2013; Orme & Huber, 2000). Furthermore, simulations can provide useful information when deciding what kind of service to implement (Orme & Huber, 2000) and DCE results can be useful to policy makers (e.g., deciding where to allocate

funds) (Phillips et al., 2002; Ryan, 1999). These advantages are partly attributed to the design and methodology of DCEs (Phillips et al., 2002).

While there are many benefits associated with DCEs and conjoint approaches, there are some other factors to consider when deciding whether or not to use this approach. Outlined below are some issues that have been raised in various articles that have used DCEs or conjoint analysis to solicit preferences in healthcare (Louviere & Lancsar, 2009; Phillips et al., 2002; Ryan & Farrar, 2000; Ryan, 1999). (1) While attributes are typically decided upon by a particular research or policy question, attribute levels are more difficult to define (Louviere & Lancsar, 2009; Ryan & Farrar, 2000). (2) DCEs often have many possible combinations of choice sets, making it nearly impossible to present all possible choices to respondents (Ryan & Farrar, 2000). (3) There is also the problem of dealing with inconsistent responders or those who do not trade off attributes. (4) Conjoint methods can be construed as more cognitively demanding than other, more traditional, methods (Phillips et al., 2002). (5) Conjoint methods are also time consuming and resource- heavy for the researchers (Phillips et al., 2002).

### 4.3 Limitations

The surveys each had their own specific limitations, along with some more general considerations of DCEs and conjoint methods. Future directions – including proposed solutions to some of these limitations – will follow.

**4.3.1 Survey limitations**. The surveys had a similar design and structure; thus, the survey limitations will be amalgamated into one section, rather than separated by study. First, the surveys asked participants to respond as though they were answering on

behalf of young people experiencing emerging mental illness (i.e., accessing EI services for the first time). These studies aimed to discover which attributes would encourage those with emerging mental health problems (e.g., mainly youth) to contact and remained engaged in EI services. That being said, the number of youths who completed the actual surveys was quite limited (e.g., 37.1% of respondents fell within ages 16 – 35 for the first survey, and 30.7% of respondents fell within the same age range for the second survey). It is important to note that segment membership in the first survey did not vary as a function of age, and was not included as a covariate in the second survey, as it was not a significant demographic difference between segments.

Despite this, first episode and EI services typically contain numerous youth given the timing of early onset (Kessler et al., 2005, 2007). Many of the participants in our surveys had already been involved in mental healthcare and were middle-aged. As such, the responses many not fully represent the actual preferences of youth accessing EI services for the first time. However, using participants that have experience with mental health services can also be beneficial. For instance, they could provide valuable insight into service characteristics that may need improvement and those that should be prioritized. Nevertheless, replication of these studies with a more youthful sample is warranted.

Second, the majority of the respondents were already involved in traditional healthcare models given that recruitment occurred in the waiting rooms of mental health clinics. This may have resulted in a selection bias, as people who do not utilize or accept traditional models of mental healthcare were probably not involved in the studies.

Moreover, many of the people who completed the first survey also completed the second, which may compound these limitations for both studies.

Third, preferences were limited to the number of attributes and their associated levels defined for each survey. If the studies had provided additional or different multi-level attributes, the preferences would obviously have differed. In terms of the second survey, specifically, having diverse options may have affected the segments' intent to use EI services, as well. Furthermore, each survey asked a very specific question: "Each choice presents three services people could contact to get help with mental health problems. Choose the service people would be most likely to contact" (survey 1), and "choose the service that would encourage people to stay in treatment for their mental health problems" (survey 2). Replicating these studies with different attributes and asking the questions in a different manner may yield different results.

Fourth, while RFC simulations may be useful, they are based on hypothetical models of mental health services. As such, financial barriers, policy restrictions, or feasibility may hinder the actual design of the services simulated. This may also affect the rate at which these services are accessed. There are also some limitations related to the study design and to conjoint methods in general, which have been expanded upon below.

**4.3.2 Deciding on attributes.** There are some limitations associated with the attributes and levels that need to be addressed. For instance, attributes and levels are typically determined in focus groups or key informant interviews (Louviere & Lancsar, 2009); however, this could lead to potential biases. Louviere & Lancsar (2009) suggest a

more systemic approach, such as iterative testing, to avoid any confounding factors. Furthermore, because attributes and levels are, in part, decided upon in discussions and focus groups, they may be subject to group membership and prevailing current social and political views. This is a strength (e.g., reflects the viewpoints of patients today) as well as a limitation (i.e., may not be representative of people who grew up with a particular set of values and priorities) of the study. Replication across discussion groups will tap into varying perspectives.

The definition of the attributes may also present a problem, as respondents may define them differently. To avoid this, Ryan (1999) suggests using quantitative information where possible (e.g., clinic is open: [a] four nights a week, [b] five nights a week, etc.) rather than qualitative (e.g., clinic is open: [a] a few times a week, [b] several times a week). When it is not possible to use quantitative information to define attribute levels, the author suggests interviews or visual aids as an alternative way to collect data (Ryan, 1999).

**4.3.3 Overwhelming options.** The number of scenarios that DCEs provide can often be overwhelming. It is not possible to ask respondents to choose between all possible scenarios; thus, a partial profile design is applied to the study design and respondents are assigned 18 possible choice sets. There are different methods to eliminate the number of choices presented in a conjoint survey design. For example, Ryan and Farrar (2000) had 16 scenarios in their study, which led to 120 options; thus, they compared the current situation in healthcare to the other 15 scenarios. Research needs to be done on how accurate the results are when using this method (Ryan & Farrar, 2000).

**4.3.4 Inconsistency in responses**. There is also the issue of what to do about inconsistent responders or those who do not trade off attributes. Some researchers choose to leave inconsistent respondents out of their analyses (Ryan & Farrar, 2000); however, it is important to consider the possibility that these respondents are making decisions in a rational way. If this is the case, these respondents should be kept in the analysis to avoid bias (Ryan & Farrar, 2000). Future DCEs could involve options that allow the respondents to remain neutral or decline to choose any of the options offered (Louviere & Lancsar, 2009; Ryan, 1999). While this may partially eradicate inconsistent responders, doing so could also be problematic. For instance, people may choose to remain neutral or decline to respond throughout the survey, due to fatigue or unwillingness to complete the survey (Streiner & Norman, 2008). In order to further reduce inconsistent responses, survey respondents should be adequately informed regarding the service or product they are being asked to comment on (Ryan, 1999).

**4.3.5 Cognitive demand for respondents.** Conjoint techniques may be cognitively demanding or difficult for some respondents. Maddala, Phillips, & Johnson (2003) conducted an experiment to identify whether simplifying conjoint tasks would be advantageous. The researchers administered two conjoint conditions to 353 participants. In one condition, there was more overlap of attribute levels (e.g., approximately two levels remained the same within the presentation of different scenarios). In the other, there was minimal overlap (e.g., all of the attribute levels could vary). The researchers found that a higher percentage of respondents in the minimal-overlap condition (32%) focused on key attributes to simplify the choice tasks, compared to those in the increased

overlap condition (23%) (Maddala et al., 2003). Important to note is that neither of the two study designs discussed in Chapters 2 & 3 allowed overlap for the choice tasks.

Using minimal overlap designs may encourage more heuristic or simplifying behaviours. For example, if someone is intensely set on the colour 'blue' for their car, then it will not make a difference what other attributes the colour is paired with. As a result, researchers would be unable to determine how important other attributes are to this respondent. Minimal overlap designs may in fact, prevent insight into preferences at the individual level. However, when these simplification strategies are seen over the majority of the sample, estimates for the entire population may be accurate ("Cautions regarding minimal overlap designs and CBC," 2008, *The CBC system for choice-based conjoint analysis*, 2013).

**4.3.6 Time consuming and resource-heavy**. Finally, DCEs utilize substantial time and energy for the researchers conducting these experiments, in terms of planning time, attribute research, focus groups, etc. As such, it is important to do a cost-benefit analysis of whether a DCE is the most appropriate method to use for a specific research question.

**4.4 Future directions**

Many of the limitations discussed provide opportunity for future research and modification of the current conjoint methods. Some suggestions for future research specific to the surveys will be outlined below, followed by some more general suggestions.

**4.4.1 Future directions specific to the study limitations**. The first limitation associated with the surveys is that the majority of the respondents do not match the intended target of EI mental healthcare (i.e., youth experiencing emerging psychiatric symptoms). Moreover, the second limitation addressed the fact that the people included in the surveys are already involved in mental healthcare services. As such, the study should be replicated with a more representative sample (e.g., those at risk of developing mental illness, but who have not yet accessed services).

Some research provides information on what young adults may prefer in terms of information regarding mental illness. Cunningham et al. (2013) conducted a prospective conjoint study to identify the most preferred strategies for providing information to young adults regarding anxiety and depression. Their findings were similar to the two survey studies. Three segments were identified, one of which was named the *Virtual* segment (28.7% of the sample), who preferred media delivery of information, such as the Internet. The *Conventional* segment (30.1%) preferred a more traditional approach to information dissemination, including books, pamphlets, and doctors' recommendations. Finally, the *Low Interest* segment (41.2%) were less intent on using information, though they were very sensitive to time demands. The authors conclude by saying that a range of strategies, such as a mixed media approach, would be beneficial. Moreover, they state that mental healthcare strategies should be based on the preference data from conjoint studies, rather than demographic differences (Cunningham et al., 2013).

There are certain algorithms that can determine who is at risk for developing psychosis (Cannon et al., 2008); thus, it may be possible to gather a sample who is

deemed at risk, but is not yet exhibiting symptoms. Furthermore, replication of these results should happen in various geographical locations, urban and rural settings, and among diverse cultures to determine the specific preferences of more heterogeneous samples.

Within future replications, there should also be an effort made to include multi-level attributes that were not included in these studies. The preferences elicited from the conjoint methods are constrained by the attributes within the choice tasks. As such, designing future conjoint surveys should be informed by previous results. Over time, determining attributes and attribute levels can be done from an empirical standpoint (e.g., the data from past conjoint research on mental health), rather than a qualitative one (e.g., focus groups). Given the discrepancy between the opinions of patients and professionals, these studies should be replicated using validated attributes to determine whether there is still a significant divergence of perspectives between these groups.

Along with this, asking specific research questions may also limit the preference results. While this is necessary for the individual purpose of each survey, it may be worthwhile to ask a broader question to a more heterogeneous sample (e.g., what characteristics of mental health services would be useful for those with emerging mental health problems?). In asking a more general question first, one could find empirically justified attributes to include in DCEs that ask more specific questions, and could be a useful addition to replicating the results of these two studies.

The limitations associated with RFC simulations (i.e., RFC simulates hypothetical models that may not reflect real-world feasibility or decision-making of treatment-

seeking individuals) also provide an opportunity for future research. If possible, the simulated models should be implemented, and patient contact, attendance, and adherence monitored. The observed data can then be compared to the predicted RFC results. Despite this, the issue remains that the simulated models' implementation, as well as real world utilization, could be hindered by availability, advertising, resources, etc.

Some additional research questions merit further study: (1) What follow-up treatments or supports do patients prefer or need after treatment programs terminate? (2) Does including patient preferences empower service users in a meaningful way? (3) Relatedly, can a more collaborative healthcare model in which patients have a degree of autonomy reduce stigmatizing attitudes towards those with mental illness?

**4.4.2 Additional considerations**. In terms of general issues associated with conjoint methods, some suggestions for future research are suggested. (1) Replication of conjoint studies and iterative testing should be done to ensure the most appropriate attributes and levels for one's research question. (2) Further research must be conducted regarding the simplification of DCEs, both in terms of the number of choices shown to the respondents as well as how the choice sets are presented. Potential issues with overlap should also be addressed. Moreover, continued investigation into simplifying DCEs for the researchers will also be very valuable. (3) Despite the negative opinions of some researchers regarding the use of qualitative methods, focus groups should continue to be used, especially for validating the preference data after being analyzed. Phillips et al. (2002) stated that doing so allowed them to better understand the results of their study. (4) Continue to research the complexities of heuristics used in decision-making. This is to

determine whether inconsistent responses are the result of actual inconsistencies, or whether they indicate a logical thought pattern.

### 4.5 Conclusions

**4.5.1 Implication recap**. Two surveys were administered in order to design and implement an effective EI service, specifically one that increases the rates of treatment contact and engagement in those experiencing emerging psychiatric symptoms. The implications of this research suggest that a collaborative model of healthcare will be attractive to both patients and care providers. SDM models elicit the preferences and priorities of patients, resulting in improved health outcomes and efficient treatment processes. This could also minimize the discrepancy observed between patient and professional perspectives. Providing a range of EI service options should maximize utilization as this approach will cater to a wider range of priorities and people and thereby ensure a higher likelihood of people contacting a mental health service. While this is also important for encouraging patients to remain engaged in treatment, it may be less so than for encouraging initial service contact. Providing services that are sex-specific may also be an important policy to put into practice, as men and women may have differing risk factors, treatment needs, and priorities (Afifi, 2007). Patients with MDD were found to have different treatment concerns, depending on their sex as well (Schuch et al., 2014). EI services that provide fast and accessible healthcare is also important. Both study's results suggest that treatment programs with shorter wait times that are readily available and minimally time-consuming will be most preferred. Such services would likely increase service engagement and reduce dropout rates. In this vein, e-health models may

be a feasible solution, given that half of the surveys' respondents were predicted to prefer this mode of service delivery. While DCEs are relatively new to the mental health field, their popularity is growing. As such, there is a high potential for conjoint analysis methods' strengths to be enforced and for the potential limitations of these approaches to be improved.

**4.5.2 Future directions recap**. Future research should focus on replicating the results of these DCEs with more heterogeneous and representative samples from a variety of locations and cultures. Moreover, replications should include a variety of different and validated attributes. In this regard, it may also be useful to begin with broad research questions to determine the main attributes, which can then be broken down into more specific research questions. Designing a service based on the RFC simulation results and then monitoring the actual usage of this service may be worthwhile to determine the reliability of RFC findings. It would also be valuable to examine the TPB results of conjoint surveys and establish whether individually tailored EI services may augment one's intent to utilize services. Some specific research questions, pertaining to patients' needs after treatment programs terminate (if applicable) and to patient empowerment and stigma reduction, have also been suggested.

There is also some opportunity to study the improvement of conjoint methods. Replication of conjoint methods and DCEs are vital to this important technique of soliciting preferences. Not only will this validate the method scientifically, it will also aid in choosing attributes and levels for subsequent research on similar topics. Moreover, finding ways to accurately specify attributes will ensure that the utility is also accurately

measured. Finding ways to simplify DCEs for both the respondents and for the researchers should be tested and evaluated to maintain the accuracy of the results. Using a mixed-methods approach (e.g., quantitative and qualitative methods) will prove valuable in further understanding study results and DCEs overall. In addition, understanding the complex mechanisms that are used in decision-making is important to determine what to do with inconsistencies within the data and ensure minimal bias by including all possible respondents.

**4.5.3 Overall assessment of DCE and its utility for mental healthcare**. DCE techniques are useful for eliciting preferences for mental health treatment services. Nevertheless, these methods are still somewhat in the early stages and are lacking validation. As already mentioned, replication is needed. According to Phillips et al. (2002), researchers measuring the value of healthcare should be mindful of the advantages and disadvantages of the various methods of determining people's preferences. While DCE methods do have some issues associated with them, a conjoint approach was an excellent method to use for the research outlined in this thesis. Furthermore, this thesis also provided many solutions as well as suggestions for future research regarding the limitations associated with DCEs. In closing, I would advocate for the utility of DCE methods in soliciting patient preferences in mental health. These methods provide a robust method of soliciting the preferences of divergent groups, including those suffering from mental illness. Using DCEs can eradicate many of the issues associated with other survey methods, such as ranking or rating. Moreover, these methods allow for advanced statistical analyses to be conducted, allowing for a thorough

look at the subgroups within the sample and determining which EI mental health service

model would be most utilized.

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