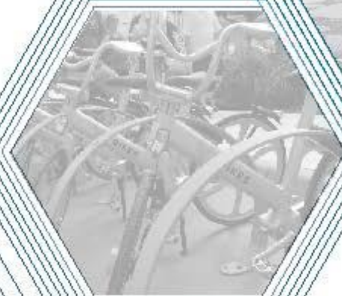

Exploring the Role of Transportation on Cancer Patient Decision-making through Machine Learning Techniques

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FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

EXPLORING THE ROLE OF TRANSPORTAION IN CANCER PATINET DECISION-MAKING THROUGH MACHINE LEARNING TECHNOQUES

FINAL PROJECT REPORT

By:

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Transportation barriers are often considered as critical factors that influence healthcare accessibility and cancer patients' decision-making regarding treatments or post-treatment process. Moreover, the built environment and lack of access to affordable and efficient transportation would significantly affect the quality of life of patients with chronic diseases such as cancer. The main goal of this study is to investigate the role of transportation in cancer patients' decision-making. Besides, this study aims to understand how built environment attributes influence the patients' quality of life (QoL). To achieve these goals, a survey was designed and conducted, and collected data were analyzed using methods from recent advances in data science. Using structural equation models (SEMs), we explored the effects of the built environment and travel distance on tumor-free years. We found that longer travel distance to radiotherapy provider is positively associated with greater tumor-free years after radiotherapy. Furthermore, machine learning models, i.e., logistic regression, random forest, artificial neural network, and support vector machine, were employed to evaluate the contribution of travel behavior and burdens on stopping or continuing radiotherapy and chemotherapy. Results reveal that lack of access to transportation has a significant impact on cancer patients' decision to stop/continue treatment. Also, limited access to private vehicles contributes to the stopping of radiotherapy treatment. Finally, we evaluated the effects of sociodemographic attributes and health-related factors along with the residential built environment, including density, diversity, design, and distance to transit and hospitals on the self-reported QoL in cancer patients after treatment. The results from machine learning models indicated that the travel distance to the closest large hospital, perceived accessibility, distance to transit, and population density are among the most significant predictors of the cancer patients' QoL. This study also has important implications for policy interventions.

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Abstract

Cancer patients face different challenges in terms of making decisions, from diagnosis to treatment and survivorship. Transportation barriers are often suggested as the critical factors that influence healthcare accessibility and the cancer patients' decision-making regarding treatments or post-treatment process. Travel distance could impact patients' decisions in terms of choosing between the appropriate or preferred treatment choices. Moreover, the built environment and lack of access to affordable and efficient transportation would significantly affect the quality of life (QoL) of patients with chronic diseases such as cancer. However, the effects of the transportation barriers on cancer outcomes, patients' decision-making towards following the treatment, and finally, their QoL are still unclear.

The main goal of this study is to investigate the role of transportation in cancer patients' decision-making and QoL. To achieve this goal, a survey was designed and conducted, and collected data were analyzed with methods from recent advances in data science. Specifically, a cross-sectional survey of cancer patients across the US was conducted to collect data related to two types of treatments, including radiotherapy and chemotherapy, and patients' health care providers. Besides, the survey contained comprehensive questions regarding personal and health-related factors while emphasizing the role of travel behavior and burdens on stopping or continuing treatments and self-reported QoL. By employing geographic information systems (GIS), we geocoded the patients' home and healthcare provider locations and calculated travel distance from home to care providers. We also collected the residential built environment attributes, including density, diversity, distance to transit, and street design.

Using structural equation models (SEMs), we explored the effects of the built environment and travel distance on tumor-free years. We found that longer travel distance to radiotherapy provider is associated with greater tumor-free years after radiotherapy. For chemotherapy, neither built environmental measures nor travel distance has a significant effect on tumor-free years.

Furthermore, machine learning models, i.e., logistic regression, random forest, artificial neural network, and support vector machine, were employed to evaluate the contribution of travel behavior and burdens on stopping or continuing radiotherapy and chemotherapy. Results reveal that lack of access to transportation has a significant impact on cancer patients' decision to stop/continue treatment. Also, limited access to private vehicles contributes to stopping radiotherapy treatment. Although our results suggest the importance of trip frequency and trip

length to healthcare providers for both radiotherapy and chemotherapy, these factors have a more significant contribution in following or quitting chemotherapy treatment.

Finally, we evaluated the effects of sociodemographic attributes and health-related factors along with the residential built environment, including density, diversity, design, and distance to transit and hospitals on the self-reported QoL in cancer patients after treatment. The results from machine learning models indicated that the travel distance to the closest large hospital, perceived accessibility, distance to transit, and population density are among the most significant predictors of the cancer patients' QoL. Also, health insurance, age, and education of the patients are associated with the QoL.

This study also has important implications for policy interventions. Traveling the remoter distance to radio providers may enhance access to higher-volume hospitals with advanced treatment quality and surpass the potential downsides of longer travel distances. Hence, the priority should be given to strengthening strategies referring cancer patients to high-quality health centers for treatment efficiently while decreasing transportation burdens by providing access to health facilities. Implementing supportive programs that provide free rides to patients with a lack of access to private vehicles can be an effective, low-cost strategy to increase access to cancer care, particularly for low-income populations.

Since our results indicate that the majority of participants use the private vehicle as their principal mode to access to treatment facilities, future interventions should consider more available, convenient and affordable car trips through supporting ride-sharing programs in addition to public transit discounts and medical transportation services.

Moreover, there is a need to develop a QoL measurement that comprehensively counts for subjective feelings as well as objective factors in terms of patients' health condition, transportation, and built environment. The QoL measurement can be used to inform communities and local governments in policy making and evaluate the extent to which the mobility and built environment meet patients' needs with chronic diseases.

Chapter I: Introduction

1.1. Research Background

The 5-year survival rate for all cancers has substantially increased to 69 %, from 2009 to 2015, due to the advances in public health, improved treatments, and early diagnosis However, estimated new cancer cases and deaths for 2020 indicates that the number of people diagnosed with cancer will rise to approximately 1.8 million individuals in the United States (American Cancer Society. 2020). Cancer patients face different challenges regarding making decisions along the cancer continuum from prevention, screening, and diagnosis to treatment, survivorship, and even end of life.

While making decisions in the early phases might seem more straightforward, treatment decisions are more complicated due to different factors including 1) treatment-related factors such as uncertainty about the effectiveness of the methods, potential outcomes, and the side effects, and 2) patient-related factors such as access to treatment, and impacts on the quality of life during treatment. Meanwhile, transportation could play a crucial role in cancer patients' decision-making, from continuing or stopping the treatment to missing or not accepting a job offer.

The present study aims to understand cancer patients' decision-making processes while focusing on transportation barriers and burdens.

1.1.1. Cancer, Transportation and Decision-making

Cancer is a chronic illness; while patients can receive treatment and the outcomes are monitored closely, in many cases, it will not disappear entirely and therefore affects patients' whole life (American Cancer Society 2020c). Since cancer is not a contagious disease, patients may decide about the adoption and type of treatment and continuing or stopping it. The initial decision-making toward selecting the cancer treatment depends on some primary factors, including the type of cancer and treatment, duration and the frequency of treatment, stage of cancer, and patients' health conditions (American Cancer Society 2020c). Several secondary factors also affect patients' decision-makin**g**, including socio-demographic attributes (age, income level, race/ethnicity, and insurance status), treatment burden (treatment side-effects), and transportation barriers.

While the earlier studies have often addressed the impacts of distance to the healthcare providers on cancer outcomes (Salloum et al. 2012; Syed, Gerber, and Sharp 2013; Silver, Blustein, and Weitzman 2012; Spees et al. 2019; Zullig et al. 2012; Jones et al. 2008; Arcury et al. 2005; Pucher and Renne 2005), the role of transportation barriers on patients' decision-making through treatment process has received less attention in the literature. Travel distance to treatment facilities may significantly influence the patients' decision making regarding treatments or post-treatments such as postoperative irradiation, and postoperative outcomes such as survival and readmission rates (A. B. Smith et al. 2018; Wasif et al. 2016; Ambroggi et al. 2015; Athas et al. 2000). It also may result in choosing less appropriate treatments (Spees et al. 2019; Ringstrom et al. 2018; Versteeg et al. 2018; White et al. 2017; Raoof et al. 2016; Ambroggi et al. 2015; Tracey et al. 2015) or may decrease access to appropriate diagnosis methods and longer diagnostic interval (Flytkjær Virgilsen, Møller, and Vedsted 2019; Onega et al. 2016). Besides, public transit and car availability are considered as factors of deprivation level associated with lower survival rates (Jones et al. 2008). Since vehicles are the most popular travel mode particularly for residents of distant and rural areas, their access to treatment facilities could be decreased while they might not have access to other mobility modes (Spees et al. 2019; Silver, Blustein, and Weitzman 2012; Arcury et al. 2005; Pucher and Renne 2005). However, more prospective studies are required to identify the potential role of travel behavior barriers to cancer patients' decision making.

1.1.2. Cancer, Built Environment, and Quality of Life

Struggling with several burdens from diagnosis to treatment and beyond causes that a significant portion of cancer patients experience a poor quality of life (Drake 2012; Jarrett et al. 2013). Health-related quality of life is a broad concept that influences total well-being. While physical and psychological issues and side effects such as pain, nausea, stress, anxiety, and depression are the key symptoms to affect patients' life, patients also face social isolation and function loss which result in experiencing poor quality of life (Cancer Treatment Centers of America 2017; Burgess et al. 2005; Reich, Lesur, and Perdrizet-Chevallier 2008; Shapiro et al. 2001). WHO evaluates the Quality of Life (QoL) as a broad-ranging concept impact on a complex process by the person's physical health, psychological state, personal beliefs, social relationships, and their relationship to salient features of their environment (WHOQOL 1997). Although pain intensity and cancer treatment (Payne et al. 1998) are among the most significant factors to reduce patients' QOL, a few studies suggest that performing physical activity such as walking and exercise interventions may significantly result in a higher quality of life for patients with cancer history (Oh et al. 2018; Mishra et al. 2012; Ho et al. 2019; Gopalakrishna et al. 2017). Accordingly, studies suggest that a supportive built environment can overcome the barriers in the outdoor environment and improve the perceived quality of life (Rantakokko et al. 2010; Engel et al. 2016). Living in neighborhoods with mixed-land use, well-designed green areas, and pedestrian-friendliness is associated with higher levels of self-reported well-being and mental health (Kim, Subramanian, and Kawachi 2008). Although evidence reveals that built environment characteristics promote the physical activities, physical well-being, social interaction in the communities, and mental health, the impacts of residential neighborhoods on quality of life is less well recognized.

1.2. Research Focus and Questions

To fulfill the research gaps in understanding transportation barriers on cancer patients, this study seeks to answer the following research questions:

1- How transportation affect the cancer patients' outcomes?

1-1 To what extent travel distance to health care facilities influence patients' tumor-free years after radiotherapy and chemotherapy treatments?

1-2 How travel distance mediates the role of the built environment on patients' tumor-free years after radiotherapy and chemotherapy treatments?

2- How do transportation barriers influence cancer patients' decision-making in continuing or stopping treatments?

- 2-1 How do patients' travel behavior along with other personal-related and treatment-related factors impact on the cancer decision-making?
- 2-2 What are the differences between patients' decision-making in terms of radiotherapy and chemotherapy treatments when they have to cope with transportation barriers?
- 2-3 What factors form the hierarchy of cancer patients' decision-making in terms of continuing or stopping a treatment?

3-How built environment attributes affect the quality of life of cancer patients?

- 3-1 How residential built environment and travel access to health care providers influence on self-reported Quality of Life in cancer patients?

1.3. Report Organization

This report contains seven chapters. Accordingly, Chapter 1 briefly introduces the research background, gaps, and leading questions; Chapter 2 represents a comprehensive literature review. This chapter includes reviewing the concepts related to transportation barriers in getting treatments, built environment, patients' travel behavior, and quality of life. Following that, Chapter 3 focuses on the online survey, questionnaire, sampling, and geocoding process; and Chapter 4 explores the effects from travel distance on cancer outcomes. In Chapter 5, we investigate cancer patients' transportation barriers and following their treatments, and in Chapter 6, we investigate the quality of life in cancer patients while considering the built environment and travel behavior. Finally, Chapter 7 summarizes the conclusions and makes policy recommendations for future research.

Chapter II: Literature Review

2.1. Overview

Cancer is a complicated disease that multiple etiologic factors play a role in addressing its' occurrence and outcomes. Scholars have developed multi-level approaches to evaluate the etiologic agents through a hieratical level. The biological-level factors are related to cellular bio marks and inherited variables and the individual-level issues, defined as the physical activity and health-related behavior that determine the cancer types. Meanwhile, the macro-environmental-level focuses on the physical and social aspects of cancer patients, such as neighborhood characteristics, socioeconomic status, access to health, and transportation which, are reported to influence cancer risk, incidents, and mortality rate (S. M. Lynch and Rebbeck 2013). While the role of sociodemographic status and access to health facilities have been extensively explored in the literature, effects of other macro-environmental factors, including transportation and built environment, remain unknown. This chapter presents a comprehensive literature review to conceptualize the role of transportation on cancer decision-making while representing other determinants of cancer outcomes.

2.2. Transportation, Accessibility and Cancer Outcomes

2.2.1. Transportation-related Barriers in Treatment Commuting

Although cancer patients in both rural and urban settings often have similar needs, the burden originated from the treatment-related commuting to health facilities can be worse for patients or cancer patient's caregivers who reside in distant places. Long-distance commuting can impose burdens on cancer patients in various aspects, including physical, social, practical, psychological, and emotional domains. For instance, patients who must travel long distances to receive treatment often experience more severe treatment-related side effects (Loughery and Woodgate 2015). Factors such as travel distance**,** lack of access to a private vehicle or the option of driving with others, trip frequency and trip length to a healthcare provider are the most crucial treatment-related factors that impose barriers on cancer patients (Guidry et al. 1997). Transportation barriers can be also explored through patients' perceptions towards travel difficulties to get to treatment or appointment. Patients with a lack of social support and uncontrolled pains have higher odd of perceived travel burden (Zullig et al. 2012). Travel barriers and burdens can also be considered as travel costs including the monetary value of the fares or payments patients make for operating costs per kilometer driving a private vehicle, taxi, bus, commuter transit and parking (Heitman et al. 2010).

2.2.2. Centralization of the Healthcare Facilities and Cancer Outcomes

Several studies investigate the effects of health care centralization and geographical accessibility on cancer survival by focusing the travel time and the travel distance from the patients' home to the nearest primary care. Travel distance resulting from regionalization and centralization of complex cancer surgeries can impose substantial burden and barriers on those at risk of mortality (Raoof et al. 2016; A. K. Smith et al. 2015). According to the literature, the concentration of advanced cancer centers in large hospitals reduces the accessibility of patients to high-quality care services, particularly for those who settle in small towns and rural areas (Pitchforth, Russell, and Van der Pol 2002). The patients who reside in further distance from cancer specialists have longer diagnostic intervals and are less likely to use cancer treatment (Jordan 2004), they present with advanced cancer stages and grades and have more reduced survival rates (Campbell et al. 2001). Moreover, patients with longer distances to general practitioners (GPs) are hypothesized to have more delay in help-seeking from the first cancer symptoms, have a longer interval in the diagnostic pathway due to the travel barriers (Flytkjær Virgilsen, Møller, and Vedsted 2019).

Some studies hypothesize that travel distance influences patients' decision-making in choosing between the appropriate or the preferred treatment. Exploring the impacts of travel distance/accessibility on treatment choice in head and neck cancer in rural settings represent that access to treatment option could influence treatment choices (Ringstrom et al. 2018). Evaluating the patients' travel preferences indicate that about 20% of ovarian cancer patients do not prefer to be treated in a distant referral center even if they receive more survival benefits and superior clinical outcomes (Shalowitz et al. 2018).

A national study of older US patients undergoing major cancer surgeries shows that patients living in distant areas are readmitted to a different hospital other than the index hospital, and they are associate with a higher risk of death (Tsai, Orav, and Jha 2015). Hence, the fragmentation of health care can contribute to worse outcomes for cancer patients. Travel distance can be more challenging for the patients when they may receive complex surgical remotely. Researchers suggest that the readmission rate of complex surgery in colorectal cancer may reduce, mainly when patients must receive the complex surgical care remotely and challenge with travel distance from index hospitals (Kelley et al. 2018).

However, effect from the regionalization of health care on cancer outcomes is still a subject of controversy. Investigating the patients' travel behavior reveals that patients who decide to receive treatments at the academic center have shown more considerable improvement in treatment quality and survival rates than those who choose the closest hospital for their treatments (White et al. 2017). Investigation of the effects of health care regionalization on testicular cancer outcomes indicates that the travel burden strongly results in the poorer outcomes for patients living in areas distant from high-volume centers. However, the centralization of subspecialty care would increase the facility case volume and treatment and is associated with improved cancer outcomes for patients with access to these facilities (Macleod et al. 2018). Therefore, the next challenge for cancer patients is to make a balance between the advantages from survival and improved treatment and the disadvantages of additional travel distance to more academic centers. Results from a national cancer database in radical cystectomy (RC) for muscle-invasive bladder cancer (MIBC) shows that both travel distance and high-volume hospital positively influence on improved overall survival. The association between travel distance and improved cancer outcomes can be mediated by access to high volume hospitals located in farther distances. This study suggests that the benefits of presenting at a high-quality cancer center can offset the disadvantages of travel burden (Xia et al. 2018). Empirical evidence that supports the paradox about the cancer care disparities in urban and rural areas suggest that patients living far from the nearest cancer care facility may even more likely to get treatment in large hospitals compared with those who are in a close distance to care centers (Spees et al. 2019).

2.2.3. Access to Travel Modes and Cancer Outcomes

"Percentage of households with access to vehicles" that is usually used by public health scholars to measure vehicle availability, has a positive relationship with the early stage diagnosis (Parsons and Askland 2007) and receiving first-line chemotherapy (Salloum et al. 2012). Women residing in areas where more than 3% of the resident have no access to a car are less likely to have breast and cervical cancer screening (Coughlin and King 2010).

Access to public transportation facilities is another measure contributing to the cancer patients' accessibility to care providers. Some studies explore the availability of public transit services within walking distance from the patients' homes (Jones et al. 2008). Accordingly, bus and rail services within walking distance (e.g., 800 meters) from patients' residential areas are considered public transportation accessibility. For large metropolitan areas in the US, access to public transit may impose transportation barriers, particularly for vulnerable groups such as Hispanic ethnicity, women, low-income cancer patients (Coughlin and King 2010).

2.3. Transportation, Cancer and Decision-making

2.3.1. Factors Affect Stopping a Treatment

Two principal factors influence on patients' decision-making throughout the treatment process including 1) treatment-related factors such as patients' uncertainty about the effectiveness of the treatment, possible outcomes, and the side effects, and 2) patient-related factors such as costs of treatment, access to treatment, and impact on the quality of life during treatment (Reyna et al. 2015; Kuchuk et al. 2013; Amalraj et al. 2009; Hawley et al. 2008; 2007; Love et al. 1989).

Sociodemographic attributes are among the most significant factors that impact the patients' decision-making about stopping or continuing treatment. Patients with low socioeconomic status (SES) including low-income level, low education, and inappropriate insurance status and those residing in the deprived areas seem to be less likely to pursue/continue treatment, and consequently, they have worse cancer outcomes (Macleod et al. 2018; Jones et al. 2008).

Race and ethnicity are among the other influential determinants of patients' decision-making. The empirical evidence suggests that minority (Blacks, Asians, and Hispanics) patients are more likely to stop their treatment and, consequently, have higher diminished outcomes (Macleod et al. 2018; Ringstrom et al. 2018; Stitzenberg and Meropol 2010; Liu et al. 2006). On the other hand, cancer treatment, including chemotherapy and radiotherapy, can affect patients' treatment decision making (National Cancer Institute 2017).

The frequency of getting chemotherapy treatment depends on the stage and type of cancer; its schedule may include one or more days of receiving drugs by patients followed by several days without treatment, or it may consist of receiving the drugs in several days in a row or every other day for a while (American Cancer Society 2020a; National Cancer Institute 2015b). Empirical research reveals that chemotherapy has multiple physical side effects (such as nausea and vomiting, and fatigue) as well as non-physical side effects such as anxiety and depression (American Cancer Society 2020a; National Cancer Institute 2015a; Kuchuk et al. 2013; Yoo et al. 2005). Since the physical side effects may influence the patients' ability to drive, they may discontinue their treatment process due to the less access to treatment facilities such as free rides to healthcare facilities (National Cancer Institute 2015a; Zullig et al. 2012).

Unlike the chemotherapy, radiotherapy does affect the nearby cells instead of the whole body, so most common side effects of radiation include nausea, fatigue, hair loss, skin problems, swallowing difficulties (mucositis) and cognitive impairment (American Cancer Society 2020b; National Cancer Institute 2018; Teguh et al. 2009). Accordingly, while more than 50% of patients diagnosed with cancer receive radiotherapy, either alone or along with other types of treatments (American Cancer Society 2020b), the side effects can significantly impact the patients' quality of life (National Cancer Institute 2018; Khan and Alhomida 2011; Sasse et al. 2006; Jereczek-Fossa, Marsiglia, and Orecchia 2002) and their willingness to stop the treatment.

In terms of the transportation-related issues, earlier studies have only discussed the effects of travel distance on cancer outcomes such as advanced stage at diagnosis, larger primary tumor size, poorer outcomes, decreased level of quality of life and higher mortality rate (Ambroggi et al. 2015; A. K. Smith et al. 2015; Campbell et al. 2001; 2000; Liff, Chow, and Greenberg 1991). However, the literature on the effects of transportation barriers on cancer decision making is still rare. A few studies discuss the likelihood of the public transit-dependent population receiving delayed medical care and not receiving regular healthcare and missing their appointments (Rask et al. 1994). Therefore, the lack of access to mobility options such as car and public transit increases the probability for the vulnerable population not obtaining cancer screening and diagnosis (Coughlin and King 2010). Accordingly, the direct effects of travel behavior components such as trip frequency, trip length, and trip mode on treatment-related travel patterns have not been discussed through the literature.

2.4. Cancer and Quality of Life

2.4.1. Quality of Life in Cancer Patients

Cancer can influence Quality of Life (QoL) in cancer patients through multidimensional effects, including the physical side effects, socioeconomic attributes, and residential built environment. The cancer treatment and medication side effects can dramatically decrease the patients' physical ability and influence on their QoL (Miller and Triano 2008). Comparing different cancer survivors reveals that those patients with improved outcomes are more likely to have a greater level of mental and social quality of life (Ferrell et al. 1995; Mellon, Northouse, and Weiss 2006).

Literature suggests that socioeconomic status and social supports are other factors that influence cancer patients' QoL (Parker et al. 2003; Costa et al. 2017; Astrup et al. 2017). It is discussed that QoL in cancer patients can be affected by race (Sarna et al. 2002) and age at diagnosis (Cimprich, Ronis, and Martinez-Ramos 2002). Hence the literature suggests that disparities in health outcomes in different geographical areas could be a result of race and ethnicity differences (Green and Hart-Johnson 2011).

Furthermore, the built environment attributes in residential neighborhoods are another factor that can affect the QoL of individuals. Identifying residents' perceptions of neighborhood physical attributes reveals that diversity, safety, and aesthetics are associated with a higher physical and mental well-being of residents and can influence on health-related quality of life (HRQOL) (Gao, Ahern, and Koshland 2016).

The literature has deeply investigated the associations between the built environment and health-related conditions such as physical activity, obesity, and cardiovascular disease in both theory and practice (Sallis et al. 2012; Saelens and Handy 2008; Brownson et al. 2009). Earlier studies define the built environment through particular measures, including density, diversity, street network connectivity, aesthetic qualities, and access to transportation facilities (Handy et al. 2002).

A few numbers of studies discuss the effects of built environments characteristics on the level of physical activities and body mass of the cancer paints (B. M. Lynch et al. 2010; Schootman et al. 2012; Pruitt et al. 2012; Keegan et al. 2014); while the majority of empirical studies emphasize the geographical accessibility and distance to cancer care providers (e.g., Parsons and Askland 2007; Russell et al. 2011). Accordingly, the evaluation of neighborhood physical attributes on cancer outcomes is a relatively new arena that has been paid less attention through cancer studies.

2.5. Conclusion

In the literature, some physical and social aspects of cancer patients, such as socioeconomic status, access to health care facilities, neighborhood characteristics, and transportation, have been considered as factors that impact cancer risk or mortality rates. While there is ample focus on the sociodemographic and health accessibility aspects, other aspects such as transportation and the built environment have received less attention. This chapter identifies the role of transportation on cancer decision-making through an expanded literature review while considering the other determinants of cancer outcomes.

In terms of transportation and accessibility and their relationship to cancer outcomes, three critical issues have been discussed in the literature. The first was to find out how the literature identifies transportation as a barrier for trips related to treatment. Transportation may impose implied burdens on patients regarding their access and travel to pursue treatment. Accordingly, patients who need to travel a longer distance to follow up with their treatments can be influenced negatively through a variety of aspects. Second, factors such as access to a private vehicle, being able to drive with others (family members or friends), access to different modes, trip frequency, and trip length to a healthcare provider are among the most significant factors that could impose barriers on cancer patients regarding their treatment pursuit. The other important matter evaluated by literature was understanding how centralization of healthcare facilities may affect cancer outcomes. Most studies focus on travel time and travel distance to healthcare facilities to discuss centralization and its effects on cancer survival rates. For instance, it has been argued that the concentration of advanced cancer centers may limit patients' access to care services, particularly for those who settle in small towns and rural areas. Hence, the centralization of health care can contribute to worse outcomes for cancer patients. Third, it was determined how access to travel modes affects cancer outcomes. Access to personal vehicles has been identified as a factor to affect the early diagnosis and receiving better treatment options. Also, some studies mention public transit availability as another measure to affect cancer patients' accessibility to health care providers.

Furthermore, this chapter reviewed the literature regarding the role of transportation in affecting cancer patient's decision-making through identifying the role of transportation in patients' decision to stop treatment. There are two main groups of factors that may affect cancer patients to stop the treatment: treatment-related factors and patient-related factors. The literature reveals that sociodemographic attributes such as income level, education level, insurance status, race and ethnicity, and living in deprived areas will significantly affect patient's decision-making about stopping or continuing treatment and consequently will influence the cancer outcomes. In addition to the factors mentioned above, transportation-related factors may also impact cancer patients' decision-making to continue/stop their treatment. While some studies argue that lack of access to either car or public transit (as mobility options) may affect patients in terms of poorer outcomes, the effects of travel behavior on cancer patients' decision-making are not extensively identified in the literature.

Finally, this chapter investigates previous studies regarding the impacts of the built environment attributes and transportation in cancer patients' quality of life. The literature has widely discussed that cancer could affect patients' quality of life through multidimensional items, including physical and psychological side effects, social support, and socioeconomic status. Besides, the built environment attributes in residential neighborhoods are also among the influential factors that may affect individuals' QoL. While the literature broadly discusses the relations between the built environment and physical and mental well-being and health-related quality of life, the impact of neighborhood physical attributes on cancer outcomes has not been evaluated in the literature. Regarding the effects of transportation-related issues on cancer patients' quality of life, the literature.

Accordingly, the effects of the transportation barriers on cancer outcomes, patients' decision-making towards following the treatment, and finally, their QoL are still unclear. This study aims to understand how transportation barriers and travel accessibility in terms of travel distance influence on cancer improved cancer outcomes and their decision to stop or continue treatments. We also aim to identify how built environment attributes of residential environment along with travel accessibility impacts the self-reported quality of life of the patients.

Chapter III: Survey Design and Data Collection

3.1. Introduction

Following a comprehensive literature review in order to find out about the most significant aspects to affect cancer transportation barriers and their quality of life, we created an online survey and collected data from cancer patients through the U.S. Accordingly, over 900 respondents completed the questionnaire through an online surveying tool- Qualtrics. The survey provides a variety of cancer-related data, including the types of cancer patients, the most critical challenges they face, the transportation options available to them, the impacts of cancer on their QoL, and their decision-making process. The respondents contributed to the survey from almost all states across the country with relatively more participants in states with higher populations (Fig. 3.1).

3.2. Survey and the Sample

This study's survey, which contains 77 questions, is divided into five domains in order to gather the most relevant data regarding respondents' socio-demographic details, medical and surgical history, travel to health care facilities, travel to work and quality of life. The protocol for survey administration and use of data survey was approved by the Institutional Review Board (IRB) Human subject at the University of Texas at Arlington. For data collection, we used the online data surveying platform- Qualtrics.

To define the survey cohort, patients had to be eligible through screen questions. Accordingly, the respondents should meet the following three defining factors:

1) They have been diagnosed with cancer,

2) They have been treated by radiotherapy, chemotherapy, or other treatments, and

3) They are currently in remission or still seeking other treatments.

The sample includes patients above 18 years old, and the participants specified their cancer condition based on different cancer types as well. Subjects were recruited over a 2- months period from September to November 2019.

All participants provided written consent mentioning their willingness to contribute to the survey. They also were asked to be thoughtful as well as honest while responding to the survey questions. After attaining the initial data (n = 950), the research team manually reviewed the patients' records to confirm the dataset's reliability and removed the cases that completed the questionnaire in less than 600 seconds. Thus, our second round of the eligibility screening process included 750 surveys.

3.3 Survey Design

The survey incorporates five separate sections in which a variety of aspects related to the patients and the disease has been questioned. The following part introduces the main five sections of the survey and provides a detailed description of them:

1. Initial Diagnosis
2. Treatment and Transportation
    a. Radio Therapy
    b. Transportation for Radiation
    c. Chemotherapy
    d. Transportation for Chemotherapy
    e. Other treatments
    f. Transportation for Other
3. Spatial Attributes
4. Socio-demographic and economic
5. Quality of Life

3.3.1 Initial Diagnosis

In order to obtain information about participants' disease condition at the initial stage of cancer diagnosis, the survey includes questions about the stage of the cancer, grade of the cancer, number of metastatic tumors, primary site of tumor, age at diagnosis, HPV and HIV status, year and the month of cancer diagnosis for the first time of diagnosis. In addition, participants answered some questions regarding all mutations that they are aware about, all treatments other than surgery that they have received, number of tumor reoccurrence, number of tumor free years, number of surgeries they had for removing tumor and the type of surgeries they had before initial treatment.

3.3.2 Treatment and Transportation

This section includes six sub-sections based on the treatment and transportation options available to the patients. Treatment options include chemotherapy, radiotherapy and other types of cancer treatments and transportation options are divided into separate sections for each of these treatment types. While this study determines treatment options as Radiotherapy, Chemotherapy, and Other treatments, the available transportation options related to these treatment types are also being concerned. The purpose is to understand the impact of transportation on both the decision-making process and the cancer outcome regarding the appropriate treatment option.

The survey asks the same questions for each treatment type from the participants, except for a few different questions regarding the treatment type. Accordingly, this section asks the duration, frequency, and length of the treatment, as well as the side effects and the impacts of treatment on the respondent’s decision-making process.

Regarding the changes made by the diseases in patients' lives, this part asks about any pain management strategies used during the treatment by patients, any financial difficulties to pay for treatment, and any influence on patients' working abilities due to the treatment. Besides, another question asks about the effects of cancer on patients' overall quality of life. The respondents' exact address was not recorded due to privacy concerns; however, they mentioned their provider's zip codes and names.

Transportation availability is one of the most critical factors affecting patients' access to healthcare facilities, which may significantly impact their decision-making process. This section contains a variety of questions regarding transportation associated with each treatment option (radiotherapy, chemotherapy, and other treatment types). Hence, respondents in each treatment group answer questions about frequency, duration, and length of trips to healthcare providers. Also, they provide information about the available mode of transportation to access the treatment facilities. Moreover, in this section, respondents clarify their preference regarding the transportation mode, including a personal automobile, public transit, or ridesharing services (e.g., Uber and Lyft). Several additional questions ask about the availability of and access to transportation for patients. These questions ask if the respondents had access to free transportation options and if they missed treatment appointments due to the unavailability of transportation or because of the transportation cost. There are also questions about the effects of transportation on respondents' access to their job during the treatment.

3.3.3 Spatial Attributes

In the third section, the survey asks about the respondents' spatial attributes such as type of housing, duration of stay at the current location, driving distance from current location to different errands (e.g., transit and gas station, food and retail shops, grocery store, and primary health provider). While the questionnaire aims to provide approximate distance measures of respondents' residence to different errands (as mentioned above), it does not want to disclose the exact location and identity. Therefore, it asks the name and the address of the nearest gas station to the respondents' residence. We used the gas station's location for spatial analysis purposes, assuming people usually live within short distances from gas stations they regularly use. Also, participants answered a question regarding their perception of the safety of their residential neighborhood.

3.3.4 Socio-demographic and Economic

In this section, the survey aims to collect information on respondents' socio-demographic and economic attributes. Thus, it contains questions about their race, marital status, education background, employment status, annual income, type of residence (own/rented), possession of driver’s license, household size, number of cars in the household, type of health insurance, and location of their current work/school (zip code and the cross street).

3.3.5 Quality of Life

A variety of quality of life aspects is considered in this section. The respondents rank their quality of life and physical conditions at a scale of 1 to 5 (from terrible to excellent, respectively). They also responded to a question that if free/discounted rides could improve their mobility options to access to job and/or healthcare provider.

3.4. Geocoding, Mapping the Respondent’s Locations, Determining Spatial Attributes

For this survey, the respondents were not asked to provide their exact home location due to the "Human Subjects Data Security." Therefore, we needed to apply another method for geocoding patients' home locations to analyze the impacts of the built environment and accessibility to health care providers on cancer patients. Thus, the participants provided the following information to help us with this issue:

1) the closest gas station's name to their home

2) the two closest intersecting streets to the gas station

3) the gas station's zip code

By geocoding the gas station address, we could decide that the patients' home location will most likely be in a one-mile buffer area from the centroid point of the gas station, assuming that all respondents will have a gas station within a half-mile radius of their residential location.

In some cases, the respondents did not provide correct addresses of the gas station locations; therefore, those cases were removed since it was not possible to locate them on the map. We used the remaining dataset and fed it into Google MyMap[1] feature. Google MyMap can take any type of the addresses, either complete or cross streets, and draw pushpins on given locations based on the addresses. Due to some minor problems such as matching names, or mistakes in the address, Google might miss the location of a point. Therefore, to ensure every pushpin demonstrates the right location, for each case, we manually matched the name of the gas station and zip code on "Google Maps" with the name and zip code provided by the respondent. Following that, we manually recorded the latitude and longitude coordinates for each of the 685 gas station locations that we were able to map on Google.

To ensure that the nearest gas station is within the one-mile distance from the respondents' home location, we also asked each respondent about the driving distance (minute) from their home to the gas station (and other errands). The respondents whom their driving time to the gas station from their home location was more than 5 minutes were removed from our cases, assuming that the mentioned gas station by them is not within the one-mile distance from their home. To calculate the 5 minutes of travel time rings for each respondents' home location, we used Maptitude as the mapping software. Therefore, the final number of cases with built environment data above, is 589 respondents.

Moreover, we needed to ensure that the residential built environment attributes used for our analyses are those in the same location that participants received their treatment. Therefore, we verified the year or month of their moving to the current residential location with the first or last year/month of their treatments. By taking this additional step, we could say that the final extracted built environment is in the accurate residential location in terms of treatment types. After using the proxy of residential location during the cancer treatment, we finally obtained 143 cases for radiotherapy, 130 cases for chemotherapy, and 104 cases for other treatments. Since in the "other treatments" group, there is a diverse range of cancer treatments, in this study, we decided to focus on radiotherapy and chemotherapy as treatment methods for cancer patients (see Fig.3.1).

[1] https://www.google.com/maps/about/mymaps/

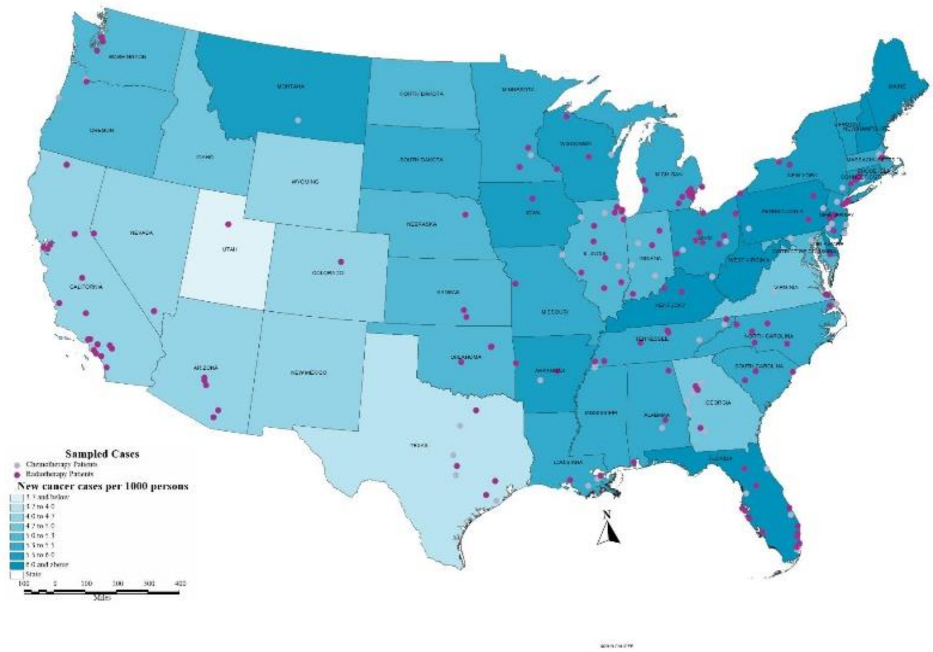

Fig. 3.1 The Geographic Distribution of the Sample

3.5. Built Environment: The “D” Variables

According to transportation studies, D variables, including density, diversity, design, and distance to transit, are introduced as the built environment attributes that can moderate travel demand. (R. Ewing and Cervero 2010). Several studies argue that in terms of travel mode and travel demand, there is a higher rate of walking or public transit use for individuals living in neighborhoods with higher density, more land-use diversity, improved street design, and better access to public transit (Cervero 2002; R. Ewing and Cervero 2010; Hamidi et al. 2015). For this study, we decided to calculate the built environment measures based on different databases.

In some of the earlier studies, the patient's home (diagnosis address) was determined by the latitude and longitude of each patient's location represented by the centroid of the address census block (e.g., Vieira et al. 2017). Some other studies used participants’ home zip codes at the time of diagnosis (cases) or reference date (control) and considered the home addresses to identify the census tract (Robert et al. 2004). In the literature, the built environment measurement is usually calculated at the block group level (Shariff-Marco et al. 2017; Conroy et al. 2017; Keegan et al. 2014); however, in this study, we measure the disaggregated built environment attributes in residential neighborhoods. Therefore, the built environment attributes of the patients' residence are calculated within a one-mile buffer zone around the participants' home location. By using a geographic information system (GIS), different datasets to the extracted buffer layers were assigned in order to calculate density, land use diversity, street design, and distance to transit as the determined built environment characteristics for our study.

The population density was calculated using the population data from ACS[2] at the census tract level. Besides, the employment density data were collected from LEHD[3] Origin-Destination Employment Statistics (LODES) for Residential Area Characteristics (RAC) (2017). From this dataset, we were able to know about the number of jobs and their distribution by NAIC sectors at the block level. Finally, the population and employment density for participants' residences were measured by overlaying the population and employment data to the extracted buffer areas.

Moreover, we computed an "Entropy Index" as our measure of land use diversity (mixed-use) within the buffer areas of participants' residences. Accordingly, we summed five sectors of jobs known as serving jobs (retail, services, food and accommodation, health, and education), for blocks within the buffer areas. Using the following equation, where P is the share of each five job sectors, and K is the number of sectors (in this case 5), we were able to compute the entropy:

$$EI = -\frac{(\sum_{k=1}^{n} P_k * lnP_k)}{lnk}$$

The value for the variable may be either 0 or 1. For the equal number of jobs in each sector, the value would be 1, and for all jobs in a single sector, this value would be 0.

To measure the distance to transit, we used the Maptitude software and calculated it based on the network distance from participants' homes to the closest public transit stops. We intended to use the network distance, meaning that we measured the actual distance a person must travel from home to a healthcare facility instead of taking an aerial/Euclidean distance. Moreover, by dividing the number of public transportations stops by the buffers' area, we estimated the transit stops density. Thus, we were able to evaluate the accessibility of the participants to public transportation.

3.6. Travel Distance to Healthcare Providers

To collect data regarding the healthcare providers' exact location, we asked respondents to provide some information including their provider name, two closest intersection streets to the provider's

[2] https://www.nhgis.org/
[3] https://lehd.ces.census.gov/data/#lodes

location, and the zip code for the facility pursuing their particular treatment type, either chemotherapy or radiotherapy. Therefore, by using the information provided by the respondents, we manually searched for all providers. Following that, we ensured that the specific provider offers cancer treatment since we did not want to use a branch of a healthcare facility that does not suggest cancer-related treatments. To find the providers' exact addresses, we used several online sources such as Google business listings, Yelp[4], and providers' online directories. As the final step, we geocoded the addresses extracted from the sources, as mentioned earlier, using Bing Geocoding API[5] to get the latitudes and longitude for each healthcare provider location for our mapping purposes.

For the next step, to calculate travel distance and time, we used Maptitude[6] as the mapping software to calculate the travel time (as minutes) from home locations to the geocoded health care providers. Accordingly, by selecting home latitude and longitude as the origin layer and the health provider latitude and longitude to as the destination layer, we created the origin and destination (OD) pairs for each participant home and health care provider addresses Following that we measured the travel distance between each pair of ODs through a limited selection. In addition, we calculated the travel time (minute) to the closest large hospital from each respondent's home location by following the shortest travel time. We decided to disregard the cases in which the travel distance to treatment facilities is more than 50 mils assuming that it is improbable for cancer patients to travel considerable distances to get frequent treatments.

[4] https://www.yelp.com/

[5] https://www.bing.com/api/maps/sdkrelease/mapcontrol/isdk/searchbyaddress

[6] https://www.caliper.com/maptovu.htm

Chapter IV: Travel Distance and Cancer Outcomes

4.1 Overview

This chapter investigates the effects of travel distance to health care providers on cancer outcomes while considering the mediating role of residential built environment. As we mentioned in Chapter III, we geocoded the patients' home and health care provider locations by using the geographic information systems (GIS) and calculated travel distance from home to care providers. We also measured the residential built environment attributes, including density, diversity, distance to transit, and street design. Using structural equation models (SEMs), we explored the direct, indirect, and total effects from key variables on tumor-free years. Considering the effects of the built environment and travel distance indicates that patients living in neighborhoods with long distances to transit and the long distance to the closest hospital are more likely to have longer travel distances to radiotherapy providers. Longer travel distance to radiotherapy provider is positively associated with greater tumor-free years after radiotherapy. For chemotherapy, neither built environmental measures nor travel distance has a significant effect on tumor-free years. Conclusions: Traveling the remoter distance to radio providers may enhance the opportunity of access to higher volume hospitals with advanced treatment quality and surpass the potential downsides of longer travel distance. Understanding the behavioral patterns of cancer patients in seeking treatment can help to promote improved cancer outcomes, particularly for those patients, reside in distant places.

4.2. Introduction

Travel distance that is a consequence of regionalization and centralization of cancer care facilities, can impose substantial burden and barriers on those patients who are at risk of mortality (Raoof et al. 2016; A. K. Smith et al. 2015). Literally, the patients who reside in further distance from cancer specialists have longer diagnostic intervals, are less likely to use cancer treatment, present with advanced cancer stages and grades, and have poorer survival rates (Jordan 2004; Flytkjær Virgilsen, Møller, and Vedsted 2019). However, effects from the regionalization of health care on cancer outcomes is still a subject of controversy.

The literature often investigates the role of travel distance in cancer outcomes in terms of survival rate, mortality rate and the cancer stage (Jindal et al. 2017; Flytkjær Virgilsen, Møller, and Vedsted

2019), and tumor-free years has not been the focus of the transportation and cancer studies. Since the association between travel distance and cancer outcome are not straightforward (Murage et al. 2017; Turner et al. 2017), statistical methods such as regression models are not able to investigate the indirect effects of predictor factors nor the interrelationships between variables. To address this research gap, we employ structural equation models to examine the mediator roles of the travel distance and trip frequency in improved cancer outcomes while investigating the independent effects of the built environment and socio-demographic attributes. We explore to what extent travel distance mediate the role of the built environment in tumor-free years after radiotherapy and chemotherapy treatments.

4.3. Methodology

4.3.1. Sample Size

The present chapter utilized data from the online survey of cancer patients after attaining the initial data (n = 950). The research team manually reviewed the patients' records to confirm the reliability of the dataset. After we omitted those patients who filled the questionnaires with the duration time less than 600 seconds, a total number of 750 surveys remained for the analysis.

In the third round of data screening, we removed the cases with more than 5 minutes driving distance from home to the closest gas station (n = 589). The participants were asked to identify the address of the closest gas station to their home. By geocoding the gas station address, we assume that the patients' home location can be located in a one-mile buffer area from the centroid point of the gas station. In order to ensure that the residential built environment was the participants' address when getting treatment, we checked the year/month of their moving to the current residential location with the first/last year/month of their treatments. Finally, we obtained 143 cases for radiotherapy, 130 cases for chemotherapy (see 3.4).

4.3.2. Key Factors

4.3.2.1. Cancer Outcome: Tumor-free Years

As we discussed in Chapter III, the survey collected data related to the participants' initial diagnosis in terms of cancer conditions before and after treatments. The participants were asked a question regarding the length of being tumor-free after following radiotherapy and chemotherapy treatments varied from less than one year to more than ten years. The higher years of being tumor-free are considered as the factor indicate the higher level of improved cancer outcomes. The literature often investigates the cancer outcomes as the survival rate, mortality rate and the cancer stage (Jindal et al. 2017; Flytkjær Virgilsen, Møller, and Vedsted 2019), and tumor-free years has not been the focus of the transportation and cancer studies.

4.3.2.2. Travel Distance to Health Care Providers

To calculate the exact addresses of health care providers for each treatment, respondents were asked about their provider name, two closest intersection streets and the zip code for their respective type of cancer treatment radiotherapy and chemotherapy treatments separately. We manually searched for every provider using the name and zip code and also confirmed if the provider offered cancer treatment using Google business listings, Yelp, Providers online directories. Then the extracted addresses were geocoded using Bing Geocoding API[7] to get the latitudes and longitude for each heat care provider. We used Maptitude[8], a mapping software to calculate the travel distance (minute) from home locations to the geocoded health care providers. We also calculate the travel distance (minute) to the closest large hospital to each respondent by following the steps below, through shortest travel distance from respondent's home location. Travel distances more than 50 mils were disregarded from the final analysis.

4.3.2.3. Built Environment Measures

This study calculated the neighborhood measures a one-mile network buffer area around the participants' home location using a geographic information system (GIS). We used population data at the census tract level from ACS[9] to calculate population density and LEHD[10] Origin-Destination Employment Statistics (LODES) in Residential Area Characteristics (RAC) (2017) for extracting employment density in the buffers. Land use diversity (mixed-use) was computed by "Entropy Index". To compute the entropy index, we used the following equation where P is the

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7 https://www.bing.com/api/maps/sdkrelease/mapcontrol/isdk/searchbyaddress
8 https://www.caliper.com/maptovu.htm
9 https://www.nhgis.org/
10 https://lehd.ces.census.gov/data/#lodes

share of job sectors (retail, services, food and accommodation, health, and education) and K is the number of sectors:

$$EI = -\frac{(\sum_{k=1}^{n} P_k * lnP_k)}{lnk}$$

The variable ranks from 0 to 1, while the value of 1 shows the equal number of jobs in each sector within the buffer, and 0 shows all jobs in a single sector within the buffer area.

Distance to transit was measured according to the network distance from participants' home to the closest public transit stops by using Maptitude software. Moreover, transit stop density was estimated by dividing the number of public transportations stops by the area of the buffers to evaluate the accessibility of the participants to public transportation.

4.3.2.4. Controlling Variables

Several studies declare that the centralization of specific cancer treatments may impose extra access barriers for certain population groups such as patients with different race, ethnicity and gender (Onega et al. 2016; Farquhar et al. 2019). We asked respondents to report their race, age at the diagnosis, and gender. We combined the race variable into a single dummy variable White versus non-White.

We also collect data related to participants' trip frequencies to the health care providers in order to get a treatment on a five-point Likert scale from 1 = less than once per month to 5 = two or more times per week.

Table 4.1 outlines the descriptive statistics of the sample based on two kinds of treatments. The majority of respondents are females and white Americans with a mean age of diagnosis from 47 to 59 years. Both radiotherapy and chemotherapy have 68 treated cases from a total of 273 participants; so, the built environment characteristics of the residential neighborhoods are slightly similar in both treatments.

The participants' trip frequencies to health care providers indicates a significant difference between the frequency of trips following two treatments. Majority of the respondents with radiotherapy, travel to their health care providers frequently at least once or more per week compare to those with chemotherapy that travel less than once every two weeks to their health providers. Radiotherapy treatment requires more frequent treatments for a period of five to six weeks (Athas et al. 2000; Sauerzapf et al. 2008).

Table 4.1. Descriptive Statistics of the Sample Characteristics Based on Treatments

	Description	Radiotherapy (n = 143)				Chemotherapy (n = 130)			
		frequency	percent	Mean	S.D.	frequency	percent	Mean	S.D.
Socio-demographic attributes									
Gender	Female	77	53.80			76	58.50		
	Male	66	46.20			54	41.50		
Race	White	123	86			107	82.30		
	Non-white	20	14			23	17.70		
Age at diagnosis				59	14			47	14
Built environment characteristics									
Population density				3765	5105			3800	6344
Employment density				2084	2678			2260	2830
Entropy index				0.67	0.03			0.67	0.04
Intersection density				164.34	88.50			166.66	91.92
Transit stop density				12.03	20.56			12.64	20.18
Distance to transit				21.59	32.93			27.78	43.38
Trip frequency to health care providers									
Less than once per month		17	11.9			9	6.9		
Once or twice a month		23	16.1			34	26.2		
About once every two weeks		15	10.5			31	23.8		
About once per week		21	14.7			32	24.6		
Two or more times per week		67	46.9			24	18.5		
Improved cancer outcome									
Tumor-free years				2.17	1.40			2.25	1.60
Travel distance				Median	S.D.			Median	S.D.
Travel distance to closest large hospital (minute)				2.34	3.54			2.36	3.95
Travel distance to the health care provider (minute)				20.07	35.34			19.23	36.47

4.3.3. Models and Statistical Analysis

The earlier literature mostly predicts the cancer outcomes as a direct function of travel distance to care providers when controlling socio-economic attributes of the cancer patients by using linear regression (Flytkjær Virgilsen, Møller, and Vedsted 2019) and Logistic and Cox regression (Murage et al. 2017; Turner et al. 2017; Jones et al. 2008). Since the association between travel distance and cancer outcome are not straightforward (Murage et al. 2017; Turner et al. 2017; Flytkjær Virgilsen, Møller, and Vedsted 2019), statistical methods such as regression models are not able to investigate the indirect effects of predictor factors nor the interrelationships between variables. To address this research gap, we therefore, analyze the mediator roles of the travel distance and trip frequency to health care providers in improved cancer outcomes while exploring the independent effects of the built environment, and socio-demographic attributes on cancer tumor-free years.

Our analysis counts for simultaneous direct and indirect associations through a mediator(s) by using the structural equation models (SEMs). This model has several superiorities over regression models, such as the possibility of simultaneous modeling of direct, indirect, and total effects of exogenous variables on endogenous variables, while also evaluating the interrelationships of the variables that cannot be identified in regression models.

The following formula explains an SEM with observed variables:

$$Y = BY + \Gamma X + \zeta$$

where:

$Y = (N_{y\times} 1)$ column vector of endogenous variables (N_y = number of endogenous variables),

$X = (N_{x\times} 1)$ column vector of exogenous variables (N_x = number of endogenous variables),

$B = (N_{y\times} N_y)$ matrix of coefficients demonstrates the direct effects of endogenous variables on each other,

$\Gamma = (N_{y\times} N_x)$ matrix of coefficients demonstrates the direct effects of exogenous variables on endogenous variables,

and ζ= $\left(N_{y\times} 1\right)$ column vector of errors (Mueller 1996).

Accordingly, the tumor-free years is an endogenous variable that is affected by exogenous variables of residential built environment characteristics and socio-demographic while mediating through travel distance and frequency of trips to radiotherapy and chemotherapy providers.

Using the software package of AMOS (version 26), we define the goodness-of-fit of the equation by minimizing the differences between the model-implied covariance matrix and the empirically-computed covariance matrix of the data. To develop the estimation method, we used maximum likelihood (ML), which requires the normal distribution of the endogenous variables (Harrington 2009). To reduce the analytical limitations, the variance-adjusted weighted least squares parameter estimator (WLSMV) was used as a second estimation method. Moreover, we evaluated the models' goodness-of-fit based on four indicators, including the χ^2 test values divided by the model's degrees of freedom, normed fit index (NFI), comparative fit index (CFI), and root-mean-square error of approximation (RMSEA). According to the widely accepted standards, the χ^2/df value must be less than 2, the CFI mean value must be less than 0.95, and the mean of the RMSEA average may be less than 0.1.

4.4. Results

Figure 4.1 and 4.2 depicts the path diagram for the best-fitted model; we directly copied from AMOS. The direct arrows in these figures illustrate the causal pathways, and curved arrows represent the correlations. The model matches the required assumption of chi-square of less than ten and an insignificant p-value (> 0.05).

4.4.1. Radiotherapy Treatment

Table 4.2 summarizes the associations between exogenous and endogenous variables. Results from the SEM indicate that amongst built environment measures, distance to transit is associated with travel distance to the radiotherapy provider. It demonstrates that living in neighborhoods with longer distances to public transit can also increase the travel distance to the radiotherapy facilities ($\beta = .192$, $\alpha = 0.02$). Moreover, distance to the closest large hospital significantly impacts the travel distance to the radiotherapy provider ($\beta = .221$, $\alpha = 0.00$). No association is observed between race, sex, and age at diagnosis and travel distance to radiotherapy providers.

As the travel distance to radiotherapy providers increases, the frequency of radiotherapy trips reduces ($\beta = - 0.159$, $\alpha = 0.05$).

Investigating the determinant factors of improved cancer outcomes reveals that travel distance to the closest large hospital negatively affects the years of tumor-free ($\beta = - 0.197$ $\alpha = 0.02$).

Results from sociodemographic attributes indicate that white Americans have greater years of tumor-free after radiotherapy treatment. Furthermore, age at diagnosis has a negative association with tumor-free years.

Interestingly, the findings indicate a positive association between travel distance and years of being tumor-free after radiotherapy ($\beta = 0.187$ $\alpha = 0.02$). It seems that patients who travel a long distance to seek radiotherapy are more probably to have improved cancer outcomes.

Results from the socioeconomic attributes on improved cancer outcomes suggest that White Americans are more likely to have more significant tumor-free years. Moreover, the age at diagnosis slightly can influence tumor-free years.

Table 4.3 illustrates the standardized direct, indirect, and total effects from key variables on tumor-free years as the final output of the model. The direct effects of travel distance to radiotherapy on tumor-free years are significantly much higher than its' indirect effects. It shows that although further travel distance to radiotherapy indirectly reduces the frequency of trips to radiotherapy, it still has a significant influence on increasing patients' tumor-free years. So, patients' cancer outcome is mostly influenced by travel distance and not travel frequency to radiotherapy providers. Accordingly, we can explain the influences of other variables on tumor-free years as well. For instance, travel distance to the closest large hospital directly reduces the tumor-free years. It also indirectly decreases tumor-free years through its impacts on travel distance and frequency of radiotherapy trips, but the indirect effects are much lower than direct effects. Total effects show that living in remote areas from the large hospital has both advantages and disadvantages. patients residing in remote areas may get higher quality treatment in farther radiotherapy centers; however, living in distant areas can reversely influence their tumor-free years. Not any significant statistical relationships were found between built environment measures and tumor-free years after radiotherapy.

Table 4.2. Path Coefficient Estimates for Effects Between Key Variables for Radiotherapy

Direct Effects Between Key Variables			**Estimate**	**S.E.**	**C.R.**	**P**
TravelTime_RadioMin	<---	Pop_Dens_1mibuff	-.030	.002	-.093	.926
TravelTime_RadioMin	<---	Employ_Dens_1mibuff	.034	.004	.110	.913
TravelTime_RadioMin	<---	EI_1mibuf	.084	74.085	1.063	.288
TravelTime_RadioMin	<---	IntsectDens_1mibuff	.006	.040	.059	.953
TravelTime_RadioMin	<---	TransStop_Dens_1mibuff	-.010	.209	-.081	.935
TravelTime_RadioMin	<---	Dis_Transit	.192	.096	2.186	.029
TravelTime_RadioMin	<---	TravelTime_Hosmin	.221	.838	2.619	.009
TravelTime_RadioMin	<---	Gender	-.004	5.956	-.050	.960
TravelTime_RadioMin	<---	Race_White	.030	8.429	.361	.718
TravelTime_RadioMin	<---	Diag_age	-.060	.216	-.696	.486
Travel_Radio_Freq	<---	TravelTime_RadioMin	-.159	.003	-1.920	.055
Radio_TumorFree_Year	<---	Pop_Dens_1mibuff	-.131	.000	-.412	.680
Radio_TumorFree_Year	<---	Employ_Dens_1mibuff	.195	.000	.640	.522
Radio_TumorFree_Year	<---	EI_1mibuf	.026	5.888	.333	.739
Radio_TumorFree_Year	<---	IntsectDens_1mibuff	-.144	.003	-1.494	.135
Radio_TumorFree_Year	<---	TransStop_Dens_1mibuff	-.055	.017	-.456	.649
Radio_TumorFree_Year	<---	Dis_Transit	-.095	.008	-1.074	.283
Radio_TumorFree_Year	<---	TravelTime_Hosmin	-.197	.068	-2.292	.022
Radio_TumorFree_Year	<---	Gender	-.124	.472	-1.473	.141
Radio_TumorFree_Year	<---	Race_White	.170	.668	2.055	.040
Radio_TumorFree_Year	<---	Diag_age	-.141	.017	-1.648	.099
Radio_TumorFree_Year	<---	Travel_Radio_Freq	.009	.150	.117	.907
Radio_TumorFree_Year	<---	TravelTime_RadioMin	.187	.007	2.209	.027

Note: see full form of the abbreviations in footnote 11.

Table 4.3. Direct, Indirect and Total Effects on Tumor-free Years for Radiotherapy

Effect from ↓ on Travel Distance	Direct effects	Indirect effects	Total effects
Pop_Dens_1mibuff	-.131	-.005	-.136
Employ_Dens_1mibuff	.195	.006	.201
EI_1mibuf	.026	.016	.042
IntsectDens_1mibuff	-.144	.001	-.143
TransStop_Dens_1mibuff	-.055	-.002	-.057
Dis_Transit	-.095	.036	-.060
TravelTime_Hosmin	-.197	.041	-.156
Gender	-.124	-.001	-.125

Race_White	.170	.006	.175
Diag_age	-.141	-.011	-.152
TravelTime_RadioMin	.187	-.001	.185
Model fit	χ^2/ df (< 2)	RMSEA (< 0.1)	CFI (>0.95)
	1.65	.06	.96

Note: see full form of the abbreviations in footnote 11.

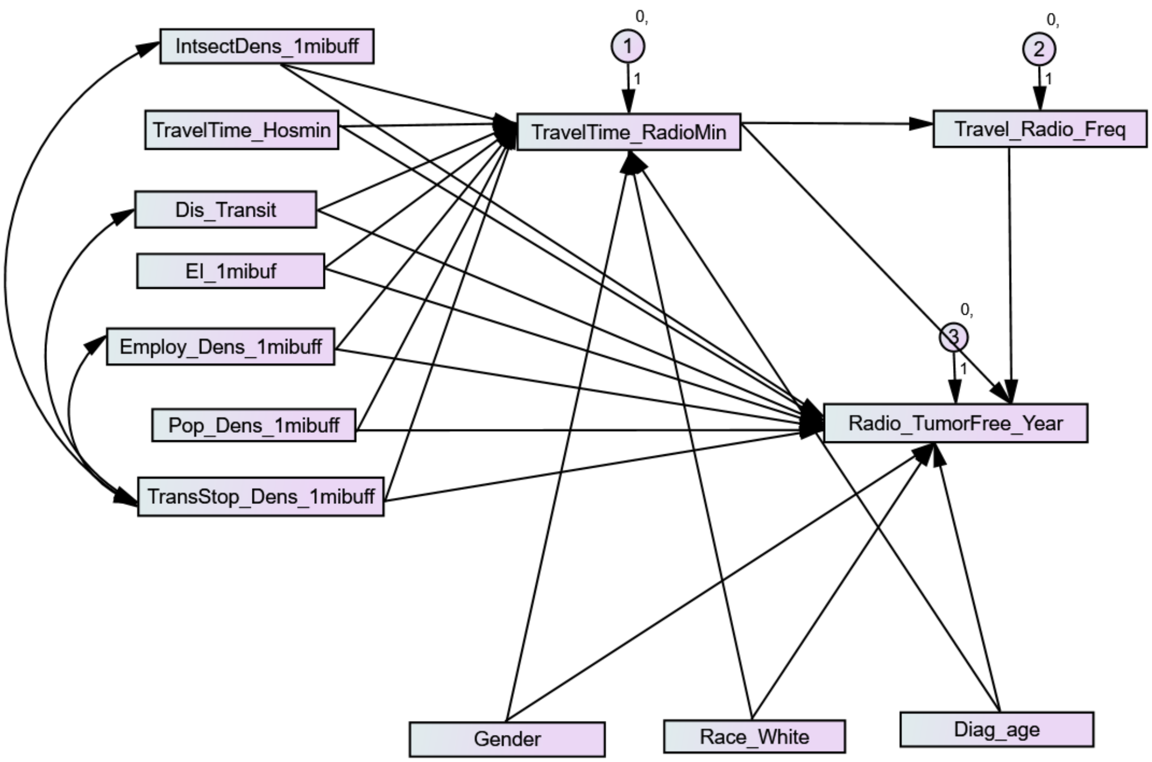


Figure 4.1. Path Diagram of Tumor-free Years for Radiotherapy[11]

4.4.2. Chemotherapy Treatment

Table 4.4 outlines the estimated coefficients of the standardized direct effects between exogenous and endogenous variables for the chemotherapy treatment. Although we could not find any statistical relationships between built environment measures and travel distance to chemotherapy providers, the travel distance to the closest large hospital significantly increases the travel distance

[11] Note: Travel-Radio_Freq: Trip frequency to health care providers (Radio), Radio_TumorFree_Year: Tumor-free years (Radio), TravelTime_RadioMin: Travel distance to the health care provider (Radio), IntsecDens_1mibuff: Intersection density, TravelTime_Hosmin: Travel distance to closest large hospital, Dis_Transit: Distance to transit, Ei_1mibuf: Entropy index, Employ_Dens_1mibuff: Employment density, Pop_Dens_1mibuff: Population density, TransStop_Dens_1mibuff: Transit Stop Density, Gender: Female, Race-White: White American, Diag_age: Age at diagnosis

to chemotherapy providers (β = .245 α = 0.00). Our findings show that female patients appear less likely to travel long distances to chemotherapy providers (β = -.236 α = 0.01). Results from the direct effects of key variables on tumor-free years after chemotherapy show that White Americans are more likely to have higher tumor-free years. As the age at the cancer diagnosis increase, the tumor-free years reduce for cancer patients with chemotherapy treatment. Travel frequency to chemotherapy providers slightly increases the tumor-free years for cancer.

Unlike the radiotherapy treatment, results show that travel distance to chemotherapy providers does not statistically influence on tumor-free years.

Table 4.5 describes the standardized direct, indirect, and total effects on tumor-free years. Similar to radiotherapy treatment, the direct effects of endogenous variables are much higher than the indirect effects from the travel distance to chemotherapy provider on tumor-free years.

Table 4.4. Path Coefficient Estimates for Effects Between Key Variables for Chemotherapy

Direct Effects Between Key Variables			**Estimate**	**S.E.**	**C.R.**	**P**
TravelTime_ChemoMin	<---	Pop_Dens_1mibuff	.423	.002	1.432	.152
TravelTime_ChemoMin	<---	Employ_Dens_1mibuff	-.275	.004	-.901	.368
TravelTime_ChemoMin	<---	EI_1mibuf	.016	78.300	.185	.853
TravelTime_ChemoMin	<---	IntsectDens_1mibuff	-.028	.039	-.283	.777
TravelTime_ChemoMin	<---	TransStop_Density_1mibuff	-.045	.214	-.414	.679
TravelTime_ChemoMin	<---	Dis_Transit	-.093	.077	-1.026	.305
TravelTime_ChemoMin	<---	TravelTime_Hosmin	.245	.862	2.703	.007
TravelTime_ChemoMin	<---	Gender	-.236	6.180	-2.850	.004
TravelTime_ChemoMin	<---	Race_White	.006	8.272	.075	.940
TravelTime_ChemoMin	<---	Diag_age	-.011	.226	-.125	.900
Travel_Chemo_Freq	<---	TravelTime_ChemoMin	.049	.003	.563	.574
Chemo_TumorFree_Year	<---	Pop_Dens_1mibuff	-.434	.000	-1.460	.144
Chemo _TumorFree_Year	<---	Employ_Dens_1mibuff	.388	.000	1.272	.203
Chemo _TumorFree_Year	<---	EI_1mibuf	-.063	6.717	-.736	.462
Chemo _TumorFree_Year	<---	IntsectDens_1mibuff	-.129	.003	-1.331	.183
Chemo _TumorFree_Year	<---	TransStop_Dens_1mibuff	.027	.018	.249	.804
Chemo _TumorFree_Year	<---	Dis_Transit	-.023	.007	-.252	.801
Chemo _TumorFree_Year	<---	TravelTime_Hosmin	-.152	.076	-1.638	.101
Chemo _TumorFree_Year	<---	Gender	-.062	.547	-.728	.467
Chemo _TumorFree_Year	<---	Race_White	.207	.710	2.412	.016
Chemo _TumorFree_Year	<---	Diag_Age	-.315	.019	-3.587	***
Chemo _TumorFree_Year	<---	Travel_Chemo_Freq	.136	.210	1.684	.092

Chemo _TumorFree_Year	<---	TravelTime_ChemoMin	.051	.008	.581	.561

Note: see full form of the abbreviations in footnote 12.

Table 4.5. Direct, Indirect and Total Effects on Tumor-free Years for Chemotherapy

Effect from ↓ on Travel Distance	Direct effects	Indirect effects	Total effects
Pop_Dens_1mibuff	-.434	.024	-.409
Employ_Dens_1mibuff	.388	-.016	.373
EI_1mibuf	-.063	.001	-.062
IntsectDens_1mibuff	-.129	-.002	-.131
TransStop_Dens_1mibuff	.027	-.003	.025
Dis_Transit	-.023	-.005	-.028
TravelTime_Hosmin	-.152	.014	-.138
Gender	-.062	-.014	-.076
Race_White	.207	.000	.207
Diag_Age	-.315	-.001	-.316
TravelTime_ChemoMin	.051	.007	.058
Model fit	χ^2/ df (< 2)	RMSEA (< 0.1)	CFI (>0.95)
	1.86	.08	.94

Note: see full form of the abbreviations in footnote 12.

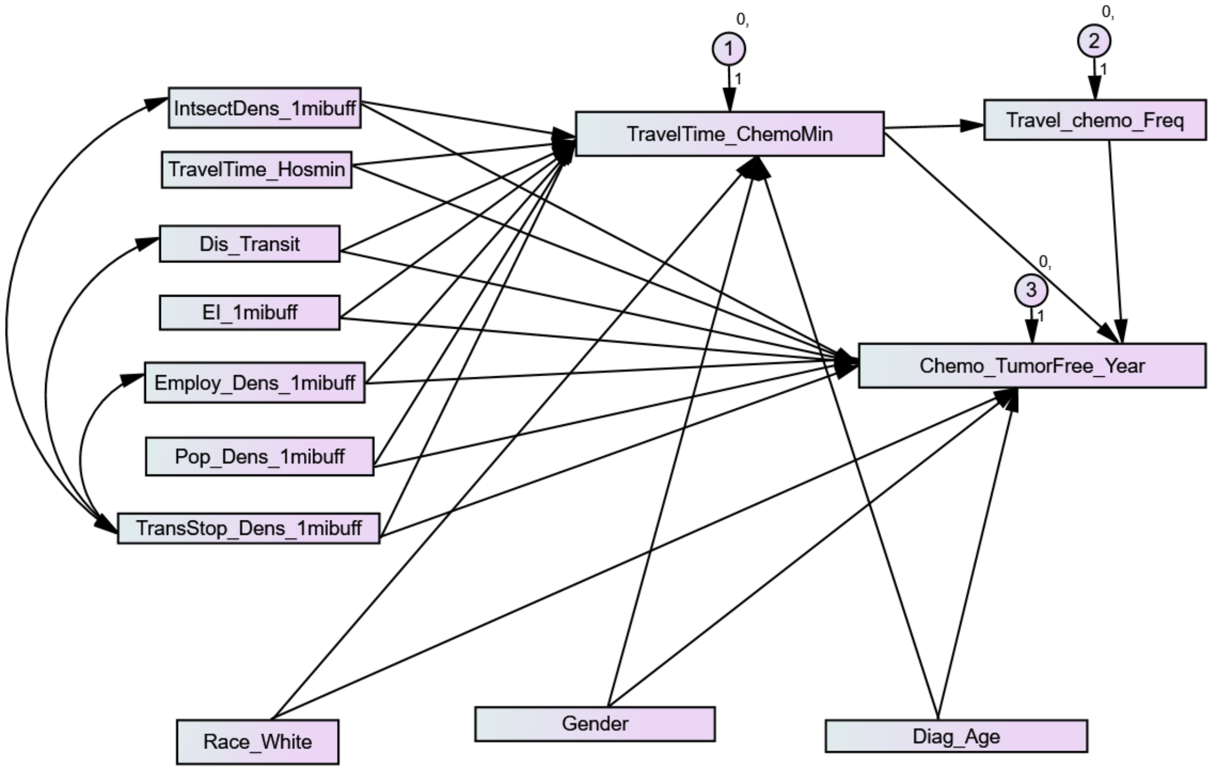


Figure 4.2. Path Diagram of Tumor-free Years for Chemotherapy[12]

4.5. Discussion

While the travel burden for cancer patients is often investigated independently, the literature has given less attention to the treatment-related travel behavior of the patients (Balfe et al. 2017; Onega et al. 2016; A. B. Smith et al. 2018). This study explores the travel distance to radiotherapy and chemotherapy while examining the effects of the residential built environment and tumor-free years. To our knowledge, no previous research has been examined the tumor-free years after treatment by mediating the role of travel distance as a transportation barrier.

The literature suggests that travel distance to health care providers reversely influence the cancer patients' outcomes in terms of advanced stage diagnosis and more risk of mortality (Farquhar et al. 2019). However, the present study reveals that travel distance to cancer facilities cannot

[12] Note: Travel-Chemo_Freq: Trip frequency to helath care providers (Chemo), Chemo_TumorFree_Year: Tumor-free years (Chemo), TravelTime_ChemoMin: Travel distance to the health care providers (Chemo), IntsecDens_1mibuff: Intersection density, TravelTime_Hosmin: Travel distance to closest large hospital, Dis_Transit: Distance to transit, Ei_1mibuf: Entropy index, Employ_Dens_1mibuff: Employment density, Pop_Dens_1mibuff: Population density, TransStop_Dens_1mibuff: Transit Stop Density, Gender: Female, Race-White: White American, Diag_age: Age at diagnosis

consistently predict the receipt of treatment in an expected way (Spees et al. 2019). The results from our analysis indicate that participants who decide to travel longer distances to radiotherapy centers have more tumor-free years. In chemotherapy treatment, the association between travel distance to provider and tumor-free years is positive but not statistically significant. Traveling the farther distance to health providers may increase the opportunity of access to higher volume hospitals with advanced treatment quality, and outweigh the potential disadvantages of longer travel distance (Xia et al. 2018). Improvement in both quality and survival rates can occur for those traveling to academic centers further from their residential areas (White et al. 2017). Accordingly, our results confirm the paradox that the centralization of health facilities might advance the cancer outcomes but also generate further burdens by imposing greater travel distance (Macleod et al. 2018).

This research is also the first study that investigates the independent role of the built environment characteristics of the patient's neighborhood when mediating the effects of travel distance to cancer care providers. Extracting D variables from residential neighborhoods, we observed a positive effect from distance to transit and actual travel distance to caner care providers for radiotherapy treatment. In transportation studies, distance to transit in which reversely indicate transit access in the neighborhoods has been proven as a measure that increases the vehicle miles traveled (VMT) per household and weekday travel distance by car per person (Frank et al. 2009; Næss 2005). Similarly, in our study, as transit access decreased, travel distance to health care providers for radiotherapy increases. However, transit access is not associated with tumor-free years.

Distance to the closest large hospital indicates the accessibility to health care services in a community. Our results show that patients living in neighborhoods with less access to large hospital are more likely to choose radiotherapy centers with farther distance as well. This finding is constant when exploring distance to chemotherapy centers. Residents of sprawl areas such as rural settings with longer distances from the nearest large cancer facility are more likely to receive treatment from the distant care providers (Spees et al. 2019). Our findings demonstrate that although patients living in sprawl areas are more inclined to refer to a distant radiotherapy center, they have fewer tumor-free years as well.

Previous research suggests that women are more likely to be treated only at a close health center when they lived more than 180 km from large public hospitals (Tracey et al. 2014), Our study shows that females are more presumable to travel longer distances to get chemotherapy treatments. Travel distance could be an important factor in women's decision-making in favor of major surgeries such as mastectomy in situations in which radiotherapy could also have been a reasonable alternative. However, for chemotherapy treatment, it seems women choose to travel long distances to treat (Ambroggi et al. 2015).

Effects from sociodemographic on tumor-free years reveal that White Americans are more likely to have improved cancer outcomes after radiotherapy treatment. This results can comply with the earlier researches propose that Non-white, Black, Asian and Hispanics patients are less interested in receiving care at high-volume hospitals comparing to white patients and are less seemingly to travel long distances to get access to cancer surgery than other races (Liu et al. 2006; A. B. Smith et al. 2018). So, White American patients who have improved outcomes may travel a long distance to get radiotherapy/chemotherapy at high volume hospitals as well.

Our study countered some limitations. The sample of this study is drawn from 750 cancer patients through the US. However, we missed approximately half of our sample patients because they did not address their exact residential location, and therefore, we had trouble in geocoding the home addresses. In terms of health provider location, we had the same problem in geocoding cancer provider addresses. Because, we explored the tumor-free years after particular treatments, so we had to separate our small samples based on the radiotherapy and chemotherapy. Another limitation is patients with other treatments that had varied categories of treatments than radiotherapy and chemotherapy, and we could not be capable of categorizing it based on a few numbers of categories and we had to exclude it from our analysis.

Chapter V: Transportation Barriers and Cancer Patients' Decision-making

5.1. Overview

Transportation barriers to health care facilities influence patients' health-related decision-making. However, the impact of travel on stopping a cancer treatment remains unclear in the literature. This chapter aims to investigate the association between cancer patients' transportation when traveling to receive radiotherapy and chemotherapy, and their decisions towards stopping or continuing treatments. In this chapter, a survey was designed and conducted to collect data from cancer patients with radiotherapy (n = 335) and chemotherapy (n = 347) in the USA regarding the factors in transportation that impact their decision-making. The survey contained comprehensive questions regarding personal and health-related factors while emphasizing the role of travel behavior and travel burdens on stopping or continuing radiotherapy and chemotherapy. Furthermore, machine learning models, i.e., logistic regression, random forest, artificial neural network, and support vector machine, were employed to evaluate the contribution of factors on predicting patients' decision-making. Results reveal that lack of access to transportation have a significant impact on cancer patients' decision to stop/continue treatment. Also, limited access to private vehicles can stop radiotherapy. Although our result suggests the importance of trip frequency and trip length to healthcare providers for both radiotherapy and chemotherapy, these factors have a greater contribution in following or quitting chemotherapy treatment. Understanding the travel behavior factors that make transportation a barrier for cancer patients, would help planners clarify the type of transportation interventions needed.

5.2. Introduction

Cancer patients face different challenges in terms of making decisions from diagnosis to treatment and survivorship. While making decisions in the early phases may look easier, treatment decisions are more complicated due to two main factors 1) treatment-related factors such as uncertainty about the effectiveness of the methods, potential outcomes, and the side effects, and 2) patient-related factors such as personal attributes, treatment costs and healthcare accessibility (Reyna et al. 2015; Kuchuk et al. 2013; Amalraj et al. 2009; Hawley et al. 2008; 2007). Transportation barriers are often suggested as the patient-related factors that influence on health care accessibility. While literature often identify the effects of travel distance on cancer outcomes, its association with patients' travel behavior such as trip frequency, trip length and trip mode have not been extensively discussed. To fill this gap, in this chapter we seek to understand how patients' travel behavior affects their decision making in terms of pursuing/continuing treatment and/or discontinuing it. Furthermore, we investigate the mediating role personal-related and treatment-related variables suggested in the literature as the significant determinants of cancer patients' decision-making. While related studies mainly focused on using simple regression models, our study further incorporated machine learning models (i.e., logistic regression, random forest, support vector machine, and artificial neural network) to delineate the nonlinear patterns underlying the predictor variables with respect to cancer patients' decision-making. Results of this study have a great potential in linking the transportation policies to public health priorities.

5.3. Methodology

5.3.1. Sample Size

As we discussed in Chapter III, the survey was totally collected data from 950 eligible participants. The research team reviewed the patients' records for quality assurance of the dataset. We omitted those patients who filled the questionnaires in less than 600 seconds. To this end, data from 750 participants remained for the analysis. In this chapter, we focused on transportation patterns of the cancer patients with radiotherapy (n = 335) and chemotherapy (n = 347), and we disregarded the respondents with other treatment types.

5.3.2. Key Factors

- *Travel behavior.* To understand cancer patients' travel behavior, the survey asked respondent to provide details about their trips to health care providers during radiotherapy and chemotherapy in terms of the frequency, the length, and transportation mode. The trip frequency was asked as follows: "how often did you make a trip to your health care provider?" Respondents could choose from a five-point Likert type scale including 1= less than once per month, 2 = once or twice a month, 3 = about once every two weeks, 4 = about once per week, 5 = two or more times per week. Querying the trip length, the survey asked respondents "how long did it usually take to get to your health care provider?", and the answers were provided in a five-point Likert type scale from less than 15 minutes" to "more than 60 minutes". In addition, we asked participants to select their main transportation mode to travel to health care provider. Seven main travel means were included in the survey: 1 = car alone, 2 = car with others, 3 = bus/rail, 4 = Free transportation services for cancer patients, 5= =taxi/cab, 6 = Uber/Lyft or similar services and 7 = Uber pool or similar services. Since the percentage of car trips (alone and with other) were considerably greater comparing to other trip modes, we converted the trip mode to a binary variable shows the car users versus non-car users (car mode = 1, other modes = 0).

- ***Treatment burdens.*** In order to identify the burdens during treatments, the survey explored the difficulties patients faced during radiotherapy and chemotherapy through four statements. Responses were given a five-point Likert-type scale (where 1= "strongly disagree" and 5 = "strongly agree") on each of the following 1-needing pain-killer to do day-to-day activities, 2-difficulties in paying treatment costs, 3-effects of treatment on ability to work, and 4-effects of treatment on ability to drive. We employed factor analysis to identify two latent factors as radiotherapy and chemotherapy burdens (maximum likelihood, 66% variance explained, KMO = 0.674, see Table 5.1). We also asked our participants about the percentage of their insurance coverage and the average treatment cost.

- ***Travel burdens.*** Another set of variables are related to transportation barriers of cancer patients during treatments. Respondents were asked four statements about how often they missed their appointments during treatment due to the lack of access to four modes of transportation including private car, public transit, app-based mobility and free transportation. The responses were provided based on a five-point Likert type scale from 1 = Less than once per month to 5 = Two or more times per week. We then factor-analyzed the four statements accessibility to different modes to one factor as lack of access to transportation (maximum likelihood, 66% variance explained, KMO = 0.674).

- ***Treatment characteristics, Treatment side effects and Cancer diagnosis.*** We asked our participants about the duration of their treatments in weeks. The responses were designed on a six-point Likert-type scale from less than two weeks to more than nine weeks. Since radiotherapy is usually given over many weeks and sometimes will be given twice a day for several weeks, we also asked about the treatment frequency in radiotherapy treatment on a six-point Likert-type scale from one day per week to more than 5 days per week. We did not ask about chemotherapy frequency, since chemotherapy treatment cannot be received as flexible as radiotherapy.

The participants were also asked about the side effects during radiotherapy and chemotherapy treatments. In the survey, we questioned the participants on a variety of side effects, including nausea, diarrhea, poor appetite, headache, dizziness and hair loss. For this study, we only considered the dizziness as it was the most significant physical side effects that impact the driving ability of the patients.

The survey includes a question about the patients' cancer type. Based on the diagnosis difficulty, we categorized the patients' cancer types into three groups: easy, intermediate, and hard to diagnose. The easiness of cancer diagnosis depends on the probability of having a positive predictive value in different cancers (Flytkjær Virgilsen, Møller, and Vedsted 2019).

- ***Sociodemographic attributes.*** The survey asked respondents about their socioeconomic characteristics, including gender, race (white American, black American, Hispanic/Latino, Asian and others), and participants' age when the diagnosis was made. These attributes were considered with respect to patients' decision making through the treatment process.

- ***Patients' decision making (stop or continue the treatment).*** As a target variable, the survey asked participants to indicate whether they stopped to follow a treatment after a while. Since a cancer patient may experience both chemotherapy and radiotherapy treatments, the survey asked about this question separately and participants had to choose the treatments from "yes" and "no" options.

5.3.3. Model and Statistical Analysis

5.3.1.1. Conceptual Framework

While most existing works follow particular approaches such as classical computational, psychophysical, dual processes and fuzzy-trace (Simon 1956; Tversky and Kahneman 1986; Epstein 1994; Reyna and Rivers 2008) to emphasize the critical role of cognitive limitations and emotional in health-related decision-making, the effects from external factors such as travel behaviors and burdens has not been studied before. To address this issue, two major external factors (i.e., treatment related factors and personal-related factors) that potentially impact the cancer patients' decision-making are investigated in this study. On one hand, we consider travel behavior, travel burdens, treatment burdens, and sociodemographic attributes as the personal-related factors since it can vary between the patients (see Fig. 5.1). On the other hand, treatment characteristic, cancer diagnosis, and side effects following approximately identified pattern based on cancer type are considered as treatment-related factors.

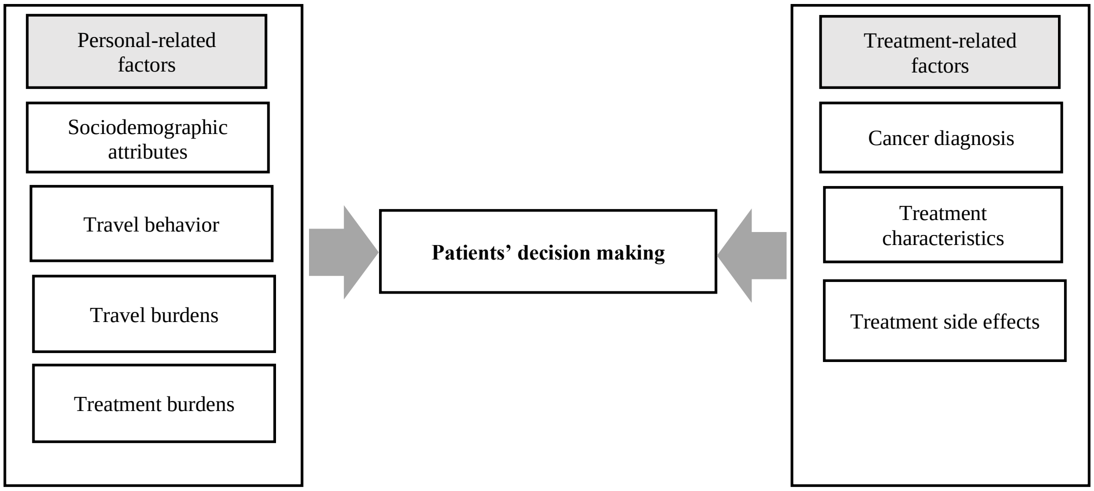


Fig. 5.1. Conceptual Framework of the Study

5.3.3.2. Machine Learning Models for Survey Data Analysis

Four machine learning models, i.e., logistic regression, random forest, artificial neural network, and support vector machine are implemented in this study to investigate the association between the decision made on stop or continue cancer treatment with personal- and treatment-related factors. Let $\boldsymbol{x} = (1, x_1, x_2, \dots, x_p)$ denotes the vector of factors (i.e., features) of one sample and y is the label with 1 represents "stop treatment" and 0 otherwise. The logistic regression model estimates the probability that $y = 1$ as:

$$Pr(\boldsymbol{x}) = \frac{e^{\beta_0+\beta_1 x_1+,\dots,+\beta_p x_p}}{1 + e^{\beta_0+\beta_1 x_1+,\dots,+\beta_p x_p}}$$

The parameter set $(\beta_0, \ \beta_1, \dots, \beta_p)$ can be obtained using maximum likelihood estimation (H. Yang et al. 2013). That is, the parameter set is estimated by maximize the conditional likelihood of y given $\boldsymbol{x}$, which is achieved by using Newton-Raphson algorithm with iteratively reweighted least squares. As a classification problem, a cut-off value 0.5 is adopted: if $Pr(\boldsymbol{x}) \geq 0.5$, the estimated label $\hat{y}$ is assigned as 1. Otherwise, it is 0.

Secondly, random forest is implemented as a classifier. Instead of growing one classification tree in the decision tree model, multiple trees are built in random forest as an ensemble. When a feature vector is given, each tree provides an estimation of the class label and the final label is obtained by majority voting:

$$\hat{y}_{forest}(\boldsymbol{x}) = majority\ vote\ \{\hat{y}_{tree}(\boldsymbol{x})\}_1^M$$

Here, $\hat{y}_{tree}(\boldsymbol{x})$ is the class label predicted by the m^{th} decision tree and there are M trees in the forest. Notably, bagging (i.e., bootstrap aggregating) strategy is used in random forest to each decision tree learners (Hastie, Tibshirani, and Friedman 2009).

The third model is artificial neural network (ANN). Also known as multilayer perceptron, ANN maps the input feature vector to a class label through multiple layers of neurons. The layers in a typical ANN model are fully connected and a weight w_{ij} is given between neuron i in one layer and neuron j in the following layer (See Appendix A). The learning process is based on the backpropagation approach. That is, each piece of data is fed through the hidden layers (forward) and each w_{ij} is adjusted based on amount of error of estimated output compared to true output (backward). Complex hidden layers in ANN facilitate the modeling of highly nonlinear patterns in the data (Kan and Yang 2011).

Finally, support vector machine (SVM) is implemented in this study to identify the connection between factors and decision made on continue or stop cancer treatment. SVM builds a high-dimensional hyperplane to separate samples into different classes, which is particularly useful when the data are with complex patterns that are not separable by a linear boundary (Hastie, Tibshirani, and Friedman 2009). Here, “support vectors” refer to samples that lie closest to the hyperplane and SVM algorithm learns the hyperplane by maximizing the margin with respect to support vectors. As such, the learned hyperplane is robust to noises and it effectively reduces the chance of overfitting (Fan, Chen, and Lin 2005).

5.4. Results

5.4.1. Sample Descriptive Analysis

Table 5.1 represents the descriptive statistics of our sample according to radiotherapy and chemotherapy treatments. Since the variety of different races in the sample is low, we categorize the participants based on white American versus non-white Americans. The averages of diagnosis age for radiotherapy and chemotherapy indicate that our patients have approximately been diagnosed in their 40’s.

The results indicated that more than 50 % of the participants travel to their health providers once, twice or more per week for radiotherapy. For chemotherapy, more than 58 % of respondents travel about twice per month or more to receive treatments. The descriptive statistics reveal that more than 60 % of the respondents travel less than 30 minutes to get their radio and chemo treatments. Results from trip mode show that respondents (for both radio and chemo treatments) were interested to use private transport or with the help of friends and family members (about 85 % of chemo patients and 87 % of chemo patients). They less likely to use public transit, shared ridership and other mobility modes. Accordingly, we changed trip mode to a dummy variable that indicates car mode versus other modes.

In terms of treatment frequency, about 66 % of the respondents have to refer to radiotherapy treatments more than once per week. About 50 % of the participants has done their radio treatment in five or less than five weeks while the chemotherapy treatment takes about three to six month or even more (66.3 %). The percentage of participants with dizziness side effect are about 36 % in radiotherapy treatment and 52 % in chemotherapy. Finally, 11.6 % of radiotherapy and 15.9 % of chemotherapy patients declare that they stopped their treatments.

Table 5.1. Descriptive Statistics of the Sample Characteristics

Description		Radiotherapy (n = 335)				Chemotherapy (n = 347)			
		frequency	percent	Mean	S.D.	frequency	percent	Mean	S.D.
Socio-demographic attributes									
Gender	Female	181	54			191	55		
	Male	154	46			156	45		
Race	White	281	83.9			289	83.3		
	Non-white	54	16.1			58	16.7		
Age at diagnosis				44.62	17.36			41.82	16.74
Travel behavior									
Trip frequency	< than once per month	50	14.9			41	11.8		
	Once or twice a month	66	19.7			102	29.4		
	About once every two weeks	41	12.2			72	20.7		
	About once per week	52	15.5			80	23.1		
	Two or more times per week	126	37.6			52	15		
Trip length (minutes)	< than 15	87	26			84	24.2		
	15-30	125	37.3			131	37.8		
	30-45	63	18.8			67	19.3		
	45-60	33	9.9			31	8.9		
	> than 60	27	8.1			34	9.8		
Trip mode	Car, alone	153	45.7			130	37.5		
	Car, with others	131	39.1			171	49.3		
	Bus/Rail	14	4.2			13	3.7		
	Free transportation services	22	6.6			17	4.9		
	Taxi/cab	4	1.2			0	0		

	Uber/Lyft or similar services	0	0			9	2.6		
	Uber pool or similar services	3	0.9			2	.6		
	Missing	8	2.4			5	1.4		
Travel burden									
lack of access to transportation	Normalized factor			100	25			100	25
Treatment burden									
Radiotherapy/Chemo therapy burdens	Normalized factor			100	25			100	25
Insurance coverage (percent)	0 %	13	3.9			19	5.5		
	1%-15%	9	2.7			9	2.6		
	16%-30%	12	3.6			16	4.6		
	31%-45%	15	4.5			18	5.2		
	46%-60%	14	4.2			19	5.5		
	61%-75%	56	16.7			64	18.4		
	76%-100%	214	63.9			202	58.2		
	Missing	2	.6			0	0		
Treatment average cost									
	Less than $ 50	151	45.1			136	39.2		
	$ 51-$ 100	14	4.2			17	4.9		
	$101-$ 250	15	4.5			17	4.9		
	$ 251- $ 500	26	7.8			29	8.4		
	$ 501- $ 1000	34	10.1			38	11		
	$ 1001- $ 2000	37	11			31	8.9		
	More than $ 2000	55	16.4			76	21.9		
	Missing	3	.9			3	.8		
Cancer diagnosis	Easy	176	52.5			163	47		
	Hard	45	13.4			72	20.7		
	Intermediate	114	34			112	32.3		
Treatment characteristics									
Treatment frequency	One day per week	112	33.4	NA					
	Two days per week	72	21.5						
	Three days per week	41	12.2						
	Four days per week	10	3						
	Five days per week	87	26						
	More five days per week	13	3.9						
Treatment duration	< than 2 weeks	53	15.8	< than 3 months		94	27.1		
	Two to three weeks	44	13.1	3-6 months		141	40.6		
	Four to five weeks	69	20.6	7-9 months		46	13.3		
	Six to seven weeks	77	23	10-12 months		29	8.4		
	Eight to nine weeks	44	13.1	13-18 months		14	4		
	> than nine weeks	48	14.3	> 18 months		0	0		
	Missing	0	0	Missing		23	6.6		
Treatment side effects	Feeling Dizziness								
	Yes	123	36.7			181	52.2		
	No	212	63.3			166	47.8		
Stop treatment	Yes	39	11.6			55	15.9		
	No	296	88.4			292	84.1		

5.4.2. Classification Results

Three metrics, i.e., accuracy, recall, and F-score are calculated for performance evaluation and comparison of proposed machine learning models. Given a classification result, we can define the following:

- True positive (TP) – correctly predicted positive samples (i.e., those who stopped cancer treatment).
- True negative (TN) – correctly predicted negative samples (i.e., those who continue treatment).
- False positive (FP) – negative samples that predicted as positive.
- False negative (FN) – positive samples that predicted as negative.

Accuracy is computed as the number of correctly classified instances over the total number of instances:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Recall (also known as sensitivity) measures the ratio between the number of true positives and all positive instances:

$$Recall = \frac{TP}{TP + FN}$$

and Precision refers to the number of true positives over predicted positive instances:

$$Precision = \frac{TP}{TP + FP}$$

F-score balances the precision and recall in the classification results as:

$$F - score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

All three metrics are in the range of [0,1] and the ideal value is 1. Notably, we pay special attention to recall because we focus more on the participants who actually stopped the treatment (positive samples). Here, we randomly select 80% of samples for training and 20% for test and each result is an average of 50 replications. Please note that our data is not balanced (i.e., there are 304 patients with radiation therapy chose to continue the treatment while 41 patients stopped it. Also, there are 303 patients with chemotherapy continued the treatment while 59 chose to stop). Thus, up-sampling strategy as well as the synthetic minority oversampling technique (SMOTE) are used to first balance the two classes (Chawla et al. 2002).

Fig. 5.2 shows the performances of proposed machine learning models for cancer patients with radiation therapy. It may be noted that the four models achieve similar performances while the ANN model has the highest one with 95% accuracy, 72.7% recall, and 80% F-score. Here, three hidden layers are deployed in ANN with 12, 12, and 6 neurons, respectively. Notably, results from simpler models (logistic regression and random forest) corroborate with SVM and ANN results (random forest achieves the same recall as ANN). This indicates that the selected factors are robust for the prediction of continue/stop treatment of patients with radiotherapy.

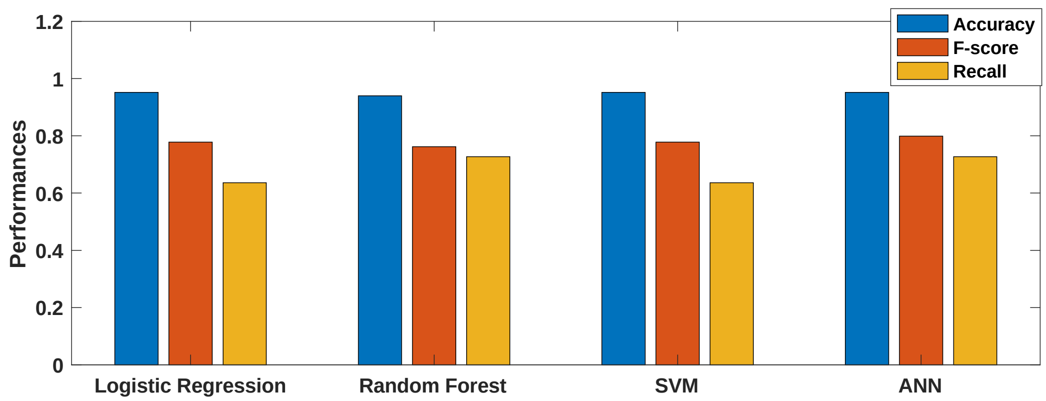


Fig. 5.2. Accuracy, F-score, and Recall of Each Machine Learning Model for Patients with Radiotherapy

Fig. 5.3 shows the performances of the four models for cancer patients with chemotherapy. Again, similar performances are achieved by four models, which indicates the robustness of selected factors (see Fig. 5.1). Here, random forest gives the best accuracy (88.5%) and F-score (64.3%). As SVM and ANN are able to model more complex relationships, they achieve better recall (78.6%) in predicting whether chemotherapy patients stop their treatment. Notably, although the accuracies and F-scores achieved by four models are lower, the best recall achieved here are better comparing with radiotherapy (72.7%).

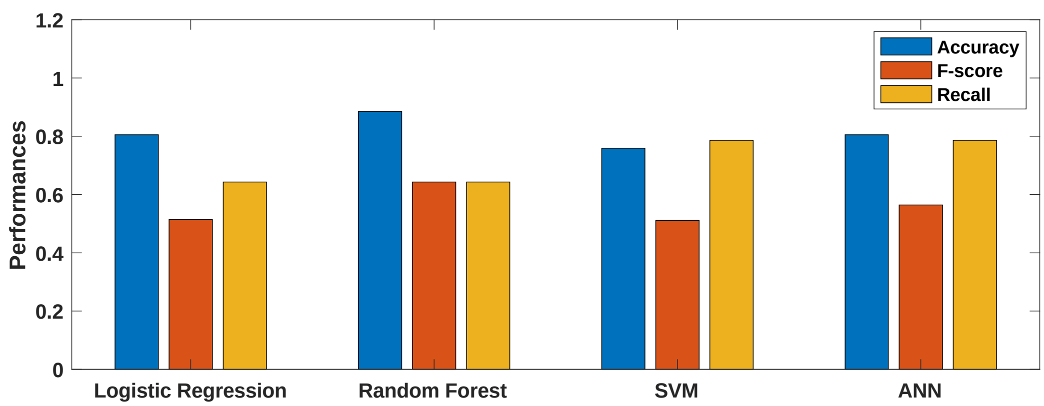
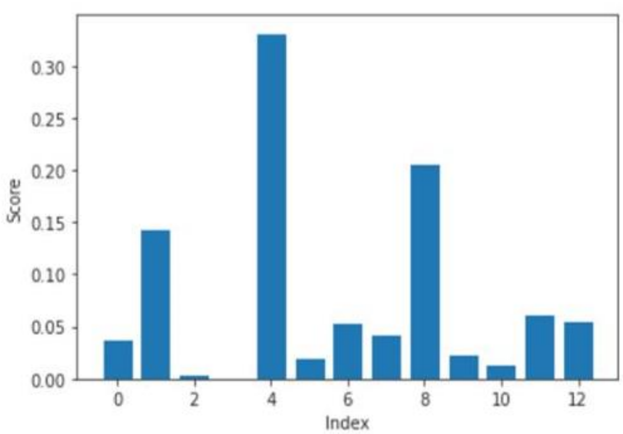


Fig. 5.3. Accuracy, F-score, and Recall of Each Machine Learning Model for Patients with Chemotherapy

Results from random forest model provides the importance of the factors contributing in cancer patients' decision-making towards continue or stopping radiotherapy treatment. As shown in Fig. 5.4, the most important feature in decision-making towards radiotherapy is lack of access to transportation, followed by insurance coverage and the age at diagnosis. Among travel behavior factors, trip frequency and trip length also make important contributions to the prediction of patients' decision-making. Treatment frequency, radiotherapy burdens, cancer diagnosis, treatment average cost, treatment duration, trip mode and gender are other features with less important effect on stopping/continuing radiotherapy.



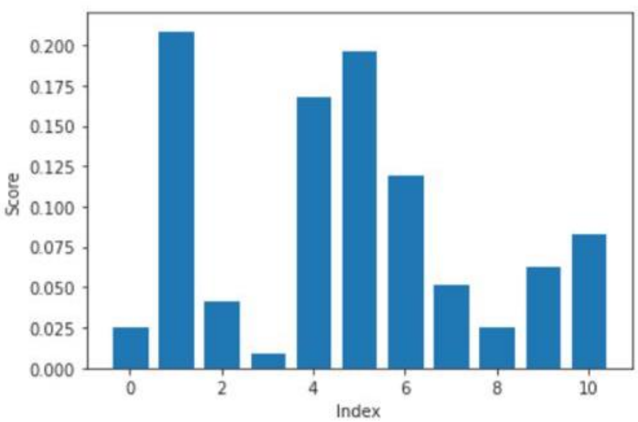
Index	Score	Feature
0	0.03824	Cancer diagnosis
1	0.14339	Age at diagnosis
2	0.00394	Gender
3	0.00000	Race
4	0.33232	lack of access to transportation
5	0.02070	Treatment duration
6	0.05494	Treatment frequency
7	0.04291	Treatment burdens
8	0.20604	Insurance coverage
9	0.02430	Treatment average cost
10	0.01456	Trip mode
11	0.06227	Trip frequency
12	0.05639	Trip length

Fig. 5.4. The Importance of Features Contribute in Continue or Stop the Radiotherapy

Fig. 5.5 shows the feature importance given by the random forest for chemotherapy. It worth be noted that age, lack of access to transportation, and chemotherapy burdens are dominant features that make the most important contributions to the decision making of chemotherapy patients. Also, insurance coverage, trip frequency and trip length can be considered as contributing features.

Moreover, to better understanding of the relationship intensity and direction of independent variables and patients' decision-making, Tables 5.2 and 5.3 illustrate the results from logistic regression and describe the most significant determinants of stopping or continuing a treatment in cancer patients. The results from logistic regression support the finding from random forest. Accordingly, lack of access to transportation is associated with stopping both radiotherapy and chemotherapy treatments. Interestingly, trip mode has a significant relationship with stopping radio treatment. It seems that patients who use car to travel to radiotherapy provider are less likely to stop their treatment comparing with those who use other travel modes. Treatment burdens and difficulty of cancer diagnosis are positively, and the age of the respondents negatively influence on stopping radiotherapy treatment. Result from the diagnosis age indicate that older adults are more likely to allow their physician make the a decision for them (Amalraj et al. 2009) and are less probable to stop radiotherapy.

In terms of chemotherapy, the treatment burdens, insurance coverage, chemotherapy average cost, cancer diagnosis and gender (female) are non-transportation factors influence on stopping treatment. This results indicate that patients with lower socioeconomic status (SES) such as insurance status are less probable to pursue/continue treatment, and their outcomes were declined in terms of survival rate (Macleod et al. 2018; Jones et al. 2008).



Index	Score	Feature
0	0.02623	Cancer diagnosis
1	0.20946	Age at diagnosis
2	0.04244	Gender
3	0.00985	Race
4	0.16841	lack of access to transportation
5	0.19736	Treatment burdens
6	0.12037	Insurance coverage
7	0.05256	Treatment average cost
8	0.02591	Trip mode
9	0.06385	Trip frequency
10	0.08355	Trip length

Fig. 5.5. The Importance of Features Contribute in Continuing or Stopping the Chemotherapy

Table5. 2. Coefficient for Each Feature in the Logistic Regression Model (Radiotherapy)

	coef	std err	z	P > |z|
Cancer diagnosis	1.5430	0.746	2.068	0.039
Age at diagnosis	-4.2787	1.416	-3.022	0.003
Gender	-0.7068	0.589	-1.201	0.230
Race	0.3483	0.657	0.530	0.596
lack of access to transportation	2.8277	1.001	2.826	0.005
Treatment duration	-0.3926	0.978	-0.402	0.688
Treatment frequency	-1.0365	0.971	-1.067	0.286
Treatment burdens	2.4205	1.067	2.270	0.023
Insurance coverage	-1.6382	0.999	-1.640	0.101
Treatment average cost	0.2938	0.818	0.359	0.720
Trip mode	-2.5017	0.711	-3.517	0.000
Trip frequency	0.5595	0.850	0.658	0.510
Trip length	1.1611	0.987	1.176	0.239

Table 5.3. Coefficient for Each Feature in the Logistic Regression Model (Chemotherapy)

	coef	std err	z	P > |z|
Cancer diagnosis	0.7249	0.287	2.525	0.012
Age at diagnosis	-0.9643	0.606	-1.591	0.112
Gender	-0.4269	0.224	-1.902	0.057
Race	0.3950	0.283	1.397	0.162
lack of access to transportation	2.7308	0.471	5.795	0.000
Treatment burdens	1.2352	0.397	3.111	0.002
Insurance coverage	-0.9861	0.382	-2.579	0.010
Treatment average cost	-0.7879	0.309	-2.546	0.011
Trip mode	-0.2616	0.300	-0.872	0.383
Trip frequency	0.0372	0.371	0.100	0.920
Trip length	0.0695	0.383	0.181	0.856

5.5. Discussion

Transportation as a fundamental need to access health care and medication could become a barrier for many people, specifically for those with chronic disease to meet their medical needs such as clinic visits, medication access, and treatment follow up, and therefore transportation barriers can lead to poorer health outcomes (Syed, Gerber, and Sharp 2013; Wallace et al. 2005). This study identifies factors that contribute to cancer patients' decision-making regarding continuing or stopping radiotherapy and chemotherapy treatments. We applied a new conceptual framework that includes personal-related and treatment-related factors while emphasizing the effects of patients' travel behavior and travel burdens in continuing/stopping a particular treatment. The random forest and logistic regression model results suggest that lack of access to transportation as a travel burden is among the most significant predictors of cancer patients' decision-making in continuing/stopping radiotherapy and chemotherapy.

Results from random forest and logistic regression reveal that poor access to transportation which suggested to play a crucial role in missing appointments (Wallace et al. 2005), seems to have a significant impact on cancer patients decision-making. This result is also in accordance with previous studies that explain travel burdens to health can be resulted from lack of access to vehicle (S. Yang et al. 2006; Silver, Blustein, and Weitzman 2012), lack of access to public transit (Pheley 1999), or even barriers in finding someone to drive them (Guidry et al. 1997).

The negative association between trip mode and stopping radiotherapy indicates that poor access to private vehicles can result in missing cancer treatment (Guidry et al. 1997) and consequently stopping it. Access to private vehicle can provide more opportunities for individuals to travel longer distances, and therefore cancer patients are more likely to receive better health care facilities (White et al. 2017) and may be less likely to discontinue their treatments. On the other hand, some studies argue that many patients who use public transportation to get medical care reported missing appointments or late arrivals compared to those who have used cars as their primary mode of transportation (Wallace et al. 2005; Rask et al. 1994).

Furthermore, results suggest that other components of travel behavior, including trip length and trip frequency to radiotherapy and chemotherapy providers, significantly contribute to cancer patients' decisions regarding continue or stop treatments. This finding is in line with the results by the earlier research suggest significant relationships between distance to providers and put off or neglecting receiving health care (Blazer et al. 1995). There is evidence that patients with a longer distance to general practitioners (GPs) are more likely to have more delays in help-seeking from the first cancer symptoms and have a longer interval in the diagnostic pathway due to travel barriers (Flytkjær Virgilsen, Møller, and Vedsted 2019). Consequently, trip length can affect the cancer patients' decision to follow up treatment.

Although our result shows the importance of trip frequency and trip length to healthcare providers for both radiotherapy and chemotherapy treatments, this factor has a greater contribution in following or quitting chemotherapy treatments. Chemotherapy treatment schedule may differ based on cancer's type and stage; it may include one or more days of receiving drugs by patients followed by several days without treatment, or it may consist of receiving the drugs in several days in a row or every other day for a while (American Cancer Society 2020a; National Cancer Institute 2015a). Hence, it can leave a variety of side effects within the patients' body including nausea, vomiting, and fatigue (Kuchuk et al. 2013) as well as non-physical side effects such as anxiety and (Yoo et al. 2005). The physical side effects may influence the patients' ability to drive, and consequently, patients may stop their treatment process simply because they cannot have access to chemotherapy facilities (Zullig et al. 2012).

Our results also confirm the literature emphasizes the importance of insurance coverage and age at diagnosis in predicting cancer patients' decision-making. Our finding confirm that poor socio economic status including insurance status of cancer patients is associated with pursue/continue a treatment and the cancer outcomes (Macleod et al. 2018; Jones et al. 2008).

This paper provides new empirical insights into the impact of transportation accessibility on cancer patients' decision-making in terms of stopping/continuing treatment. Although travel accessibility have been considered as a health barrier for cancer patients (Guidry et al. 1997), previous studies has not comprehensively examined the factors that influence on stopping a treatment. While the transportation policies are mostly favoring travel convenience, speed, and roadway expansion, the new transportation policies tend more into accessibility rather than mobility (Litman 2013). This papers' findings suggest that not only increasing access to transportation can impact on cancer patients' decisions, but also trip frequency and trip length to cancer treatments are important factors affects patients' decisions. A further contribution of this study is that traveling by car to treatment facilities decrease the probability of stopping radiotherapy treatment. Understanding the travel behavior factors that make transportation a barrier for cancer patients would help planners clarify the type of transportation interventions needed.

This study applied a comprehensive conceptual model developed based on machine learning algorithms allows us to understand cancer patients' decision-making based on personal and health-related factors. To our knowledge, these associations have not been investigated in the literature. However, working with the small sample size in our study can be a principal limitation of our study, which may have caused some failures in identifying more associations between the key variables, particularly in the logistic regression model.

Chapter VI: Examining the Impacts of Built Environment on the Quality of Life in Cancer Patients

6.1. Overview

Despite the accumulative evidence regarding the impact of the physical environment on health-related outcomes, very little is known about the relationships between built environment characteristics and quality of life (QoL) of cancer patients. This chapter aims to investigate the association between the built environment and QoL by using survey data collected from cancer patients within the US in 2019. To better understanding the associations, we controlled the effects from sociodemographic attributes and health-related factors along with the residential built environment, including density, diversity, design, and distance to transit and hospitals on the self-reported QoL in cancer patients after treatment. Furthermore, machine learning models, i.e., logistic regression, decision tree, random forest, and multilayer perceptron neural network, were employed to evaluate the contribution of these features on predicting the QoL. The results from machine learning models indicated that the travel distance to the closest large hospital, perceived accessibility, distance to transit, and population density are among the most significant predictors of the cancer patients' QoL. Also, health insurance, age, and education of the patients are associated with the QoL. The adverse effects of density on the self-reported QoL can be addressed by individuals' emotions towards negative aspects of density. Given the strong association between QoL and urban sustainability, consideration should be given to the side effects of urban density on cancer patients' perceived well-being.

6.2. Introduction

Earlier studies suggest that supportive built environment can overcome the barriers in the outdoor environment and improve the perceived Quality of life (QoL) (Rantakokko et al. 2010; Engel et al. 2016). On the other hand, the built environment effects on primary and secondary cancer prevention through spatial proximity, transportation and land use and housing (Wray and Minaker 2019).Spatial proximity and centralization of cancer care services impose travel burden to cancer patients particularly low-income and transit-oriented patients dwelling in remote areas (Pitchforth, Russell, and Van der Pol 2002; Jordan 2004; Campbell et al. 2001; Flytkjær Virgilsen, Møller, and

Vedsted 2019; Ringstrom et al. 2018). Moreover, built environments characteristics is suggested to impact on health-related behaviors such as overweight and obesity among cancer survivors (Shariff-Marco et al. 2017; Conroy et al. 2017). Access to neighborhood amenities such as recreational facilities, parks and beaches are proposed to contribute to the physical activity recommended by American Cancer Society and improve the cancer outcomes (Keegan et al. 2014). Moreover, Scholars propose that population density influence on cancer mortality (Chaix et al. 2006; Freedman, Grafova, and Rogowski 2011; Parsons and Askland 2007; Keegan et al. 2014). It seems that living in more densely neighborhoods is more associated with higher risks of cancer incidents and poorer overall survival. However, the associations between the built environment attributes and the cancer patients' QoL has not been well recognized. Understanding the factors shaping the patients' quality of life can help public health planners to recognize the vulnerable groups of patients who require further support interventions and provide appropriate services to cancer survivors (Zebrack 2000). In order to fulfill this research gap, present chapter seeks to understand how built environment attributes of residential neighborhoods count for the level of quality of life of the cancer patients. We explore the effects from built environment attributes by considering objective measures as well as the perceived neighborhood. Furthermore, and to conduct a comprehensive framework, we employ the sociodemographic attributes and health-related variables reviewed and suggested in the literature as the significant determinants of cancer patients' QoL. Recognizing the associations between residential neighborhoods and QOL help urban and policy makers to design health-oriented neighborhoods that can improve the well-being and satisfaction of residents.

6.3. Methodology

6.3.1. Sample size

In order to investigate the main aims of this chapter, we utilized survey data related to the behavioral patterns of the cancer patients during primary treatments including radiotherapy and chemotherapy, and other treatments. The questionnaire contains general information and questions related to the cancer type and the treatments, patients' residential neighborhoods as well as their perceptions, attitudes and quality of life. The third part of the questionnaire included the socioeconomic attributes of the respondents. After attaining the initial data (n = 950), we omitted those patients who filled the questionnaires within less than 600 seconds to remove unreliable entries. To this end, a total number of 750 surveys remained for the spatial analysis.

By geocoding the gas station address, we located each participant's home location in a one-mile buffer area from the centroid point of the gas station. We omitted cases with invalid home addresses that were not able to locate on the map. To ensure every pushpin was located on the right location, we manually verified each location by matching the name of the gas station and zip code on Google maps with the name and zip code provided by the respondent. As such, we geocoded latitude and longitude coordinates of 685 home address location.

Several controlling questions in the survey further helped with accurate home addresses extraction. For example, we asked participants a set of questions related to the driving distance (minute) from their homes to different errands, including the gas station. We removed those with more than 5 minutes driving from home to the closest gas station and kept the respondents that their geocoded home addresses were less than 5 minutes driving from their nearest gas stations (n = 589).

6.3.2. Key factors

6.3.2.1. Built environment measures

The built environment measures in the present study include density**,** land use diversity**,** street design**,** and distance to transit**.** Using a geographic information system (GIS), we join different datasets to the extracted buffer layers and measure the built environment attributes (see Chapter IV).

6.3.2.2. Perceived built environment and accessibility

Although supportive actual environment has been proven as a necessary factor in improving the individuals' health outcomes, studies suggest the importance of perceived environment in promoting active mobility and health-related behaviors (Ma and Dill 2015). To explore the perceived built environment, we ask the participants to evaluate their neighborhoods characteristics on five-point Likert scales where 1 = very poor to 5 =very good. Respondents state how well their residence and its location meet patients' needs through six statements in terms of easy access to their health provider, easy access to drugstores, closeness to work/school, closeness to family members, affordability of the neighborhood according to patients' income and their treatment costs, quietness, safety and security of their neighborhood according to cancer patients' mental and physical condition. We then use confirmatory factor analysis (maximum likelihood with Promax rotation with 59.54 % variance explained and KMO = 0.869) to reduce the number of the factors and extract one factor indicate the perceived built environment (see Table 6.2). We also ask respondents to evaluate their residential accessibility in terms of approximate driving distance (minute) distance from their residential built environment to six different errands. We factor analyze the distances to obtain a factor indicate the built environment accessibility (maximum likelihood with Promax rotation with 62.27 % variance explained and KMO = 0.879).

6.3.2.3. Quality of life

All our participants were selected from those patients who have been followed three types of cancer treatments. Accordingly, to identify the QoL, the survey includes a self-reported question evaluating the respondents' overall quality of life after cancer treatments in five-point Likert type from 1 = terrible to 5 = excellent.

6.3.2.4. Other key variables

Previous studies found that other key variables such as sociodemographic and health condition can also influence the QoL. For instance, low income people are more likely to have less physical activity and hence higher rates of morbidity and poorer physical function (Nilsson, Avlund, and Lund 2010). On the contrary, higher income adults are likely associated with higher levels of health-related QoL (Sallis et al. 2009). Accordingly, the survey contains self-reported questions related to the socio-economic attributes of the patients including age, gender, income, race, education, employment status, home ownership, car ownership, and health insurance coverage.

Regarding the cancer-related factors, the survey includes questions about the cancer type and the type of treatments. We categorized the patients' cancer types based on the diagnosis difficulty to three groups including easy, intermediate and hard to diagnosis (Flytkjær Virgilsen, Møller, and Vedsted 2019). Table 6.1 indicates the descriptive statistics of the key variables and table 6.2 indicate the results from the factor analysis. We also grouped patient's cancer based on radiotherapy and chemotherapy.

6.3.3. Predictive Modeling for Quality of Life of Cancer Patients

In this chapter, four machine learning models, i.e., logistic regression, decision tree, random forest and multilayer perceptron neural network are employed to investigate how built environment characteristics, perceived built environment, socio-demographic attributes and patients' health-related variables are correlated with their QoL. Notably, the QoL scores are binarized into high- or low-level of QoL using a cut-off QoL = 3. In other words, if a patient is with QoL ≥ 3, a label of "high-level of QoL" (i.e., 1), will be assigned. Otherwise, the patient will be associated with a label of "low-level of QoL" (i.e., 0). Let $\boldsymbol{x} = (1, x_1, x_2, \dots, x_m)$ denotes the feature vector of an instance (i.e., a patient) and $y \in (0,1)$ is the label. In logistic regression, the log-odds for the label 1 is calculated as:

$$\hat{p}(\boldsymbol{x}) = \frac{e^{\beta_0+\beta_1 x_1+,\dots,+\beta_m x_m}}{1+e^{\beta_0+\beta_1 x_1+,\dots,+\beta_m x_m}} = \frac{1}{1+e^{-\boldsymbol{x\beta}}}$$

The parameter $\boldsymbol{\beta}$ can be determined using the maximum likelihood estimation (H. Yang et al. 2013). As a classification problem, we adopt 0.5 as the cut-off probability: if $\hat{p}(\boldsymbol{x}) \geq 0.5$, the estimated label $\hat{y}$ is considered as 1. Otherwise, it is 0.

The decision tree model deploys a tree-like structure to learn simple decision rules inferred from the data. Starting from the root node, an instance is sorted through a sequence of internal nodes to reach a leaf node, which assigns a class label to the instance. Each internal node symbolizes a test on the instance and the path from root to leaf node can be represented as a classification rule (Hastie, Tibshirani, and Friedman 2009). Assume the leaf node h contains n_h patients, we let

$$\hat{p}_{hk} = \frac{1}{n_h} \sum_{\boldsymbol{x} \in R_h} I\{y = k\}$$

denotes the proportion of class k observations in node h. The patients in node h can be classified based on majority voting:

$$k(h) = \arg\max_k \hat{p}_{hk}$$

A few criteria can be used for splitting the internal nodes, such as cross entropy and Gini index. Notably, although decision tree is considered as a relatively simple approach, the generated classification rules are highly interpretable. Thus, it is still widely used in the machine learning community, especially among medical scientists.

An extension of the decision tree classifier is the random forest. It consists a large number of decision trees that operates as an ensemble. To ensure maximum diversity exists among the trees, the bootstrap aggregation (i.e., bagging) strategy is incorporated in the random forest (Hastie, Tibshirani, and Friedman 2009). That is, it allows each decision tree to perform bootstrap (i.e., randomly sample from the dataset with replacement) and grow a decision tree based on the bootstrapped instances. Then, the prediction of class membership is based on a majority voting process. Let $\hat{y}_t(\boldsymbol{x})$ be the predicted label from the t^{th} decision tree for an instance with a feature vector $\boldsymbol{x}$, then the final predicted label of that instance is:

$$\hat{y}_{forest}(\boldsymbol{x}) = majority\ vote\ \{\hat{y}_t(\boldsymbol{x})\}_1^T$$

where T is the total number of trees in the forest and it can be adaptively tuned by the user. Finally, a multilayer perceptron (MLP) neural network model is implemented. The MLP feature vectors in the input layer to the class labels in the output layer through hidden layers. Usually, multiple hidden layers are incorporated to handle the nonlinearity of the input data. The output layer contains 2 neurons representing the classification results (i.e., 0 and 1). The mean squared normalized error is used as the performance measure of MLP and the weight associated with each neuron is optimized based on the backpropagation approach (Kan, Chen, and Yang 2013).

6.4. Results

6.4.1. Descriptive Statistics and Factor Analysis

Table 6.1 indicate that approximately half of the sample are males, with an average of 53 years old. The majority of the cases are white American, mostly high-educated. The sample population are covered by a variety of health insurance, majority of them are converged by Medicaid and Medicare. About 83 % of the sample are categorized in easy to intermediate level of cancer diagnosis. Because cancer patients can be treated by more than one type of treatments during the remedy, the sample are able to have multiple answers. So, the distribution of three cancer treatments are slightly similar to each other. Table 6.2 indicates the factor analysis for perceived accessibility and perceived built environment. Utilizing from confirmatory factor analysis for each set of questions, we extract two main factors.

Table 6.1. Characteristics of the Study Population (N = 589)

Variables	**Description**				
		Count	percent	Mean	S.D.
Socio-demographic attributes					
Gender	Female	292	49.6		
	Male	297	50.4		
Race	White	510	86.6		
	Non-white	79	13.4		
Education	Well-educated (bachelor and above)	316	53.7		
	Less-educated (below bachelor)	256	43.5		
	Missing	17	2.9		
Employment status	Employee	220	37.4		
	Not-employee	364	61.8		

	Missing	5	.8		
Residential status	Owner	219	37.2		
	Not-owner	366	62.1		
	Missing	4	.7		
Number of cars in the household	0	45	7.6		
	1	243	41.3		
	2	217	36.8		
	3 or more	84	14.3		
Health insurance	Medicaid	96	16.3		
	Medicare	208	35.3		
	Affordable Care Act	21	3.6		
	Employer-paid insurance	142	24.1		
	Private health insurance	54	9.2		
	Uninsured	30	5.1		
	Other insurance	37	6.3		
	Missing	1	.2		
Income				50872	28132
Age				53	15.58
Household Size				2.55	1.36
Built environment characteristics					
Population density				3714	6761
Entropy index				.66	.04
Intersection density				172	96
Transit stop density				12	20
Distance to transit (min)				27.29	95.23
Travel distance to closest large hospital (min)				12	206
Perceptions					
	Perceived built environment			99.72	25.33
	Perceived accessibility			92.99	15.16
Health-related variables					
Cancer type (diagnosis)	Easy	285	48.4		
	Intermediate	203	34.5		
	Hard	72	12.2		
	Unknown	29	4.9		
Cancer treatments					
Radiotherapy	1 = having radiotherapy	266	45.2		
	0 = not having radiotherapy	323	54.8		
Chemotherapy	1 = having chemotherapy	273	46.3		
	0 = not having radiotherapy	316	53.7		
Other	1 = having other treatment	261	44.3		
	0 = not having radiotherapy	328	55.7		
Quality of life					
Overall quality of life	Terrible	17	2.9		
	Poor	67	11.4		

	Average	168	28.5
	Good	219	37.2
	Excellent	118	20

Table 6.2. Results from Factor Analysis for Perceived Built Environment

	Please indicate how well your residence and its location meet the following characteristics	*Loadings*
Perceived built environment	Easy access to your health provider	.788
	Easy access to drugstores	.797
	Closeness to your work/school	.772
	Closeness to your family members who can take care me when I need them	.730
	Affordable neighborhood according to your income and treatment costs	.805
	Quiet, safe and secure neighborhood according to your mental and physical condition	.735
	Please indicate the approximate travel distance (in minutes) from your current residence to the following errands	*Loadings*
Perceived accessibility	Closest public transit station	.517
	Closest gas station	.846
	Closest restaurant/fast food place	.905
	Closest drugstore	.896
	Closest grocery store	.889
	Patients' primary health provider	.584

6.4.2. Classification Results

In this study, two metrics, i.e., accuracy and F-score, are used for the evaluation of the performance of proposed models. Accuracy is calculated as the correctly classified instances over the total number of instances. F-score balances the precision and recall in the classification results. Precision refers to the number of true positives over predicted positive instances, whereas recall measures the ratio between the number of true positives and all positive instances (Hastie, Tibshirani, and Friedman 2009). Both accuracy and F-score are in the range of [0,1] and the ideal value is 1. Notably, we randomly select 80% of instances for training and 20% for test and each result is an average of 50 replications.

As shown in Fig. 6.1, the MLP model achieves the highest accuracy for both training (90%) and test sets (69%). It is worthy to note that the number of hidden layers and the number of neurons in each layer are tuned to achieve the best performance while avoid the effect of overfitting. Here, three hidden layers are deployed with 12, 12, and 6 neurons, respectively. The random forest model achieves a training accuracy of 81% and a test accuracy of 60%, which are slightly better than the decision tree model. However, the obtained decision tree contributes to the interpretation of the importance of the feature variables. As shown in Fig. 6.1, the simplest model, i.e., logistic regression, achieves 66% and 61% accuracy for training and test, respectively. This can be used to benchmark and corroborate the results from other models. Notably, the best accuracy for test data achieved is ~70%. This is due to the high heterogeneity of cancer patients within each group (i.e., high-level QoL and low-level QoL) as we binarized the continuous QoL scores from the survey.

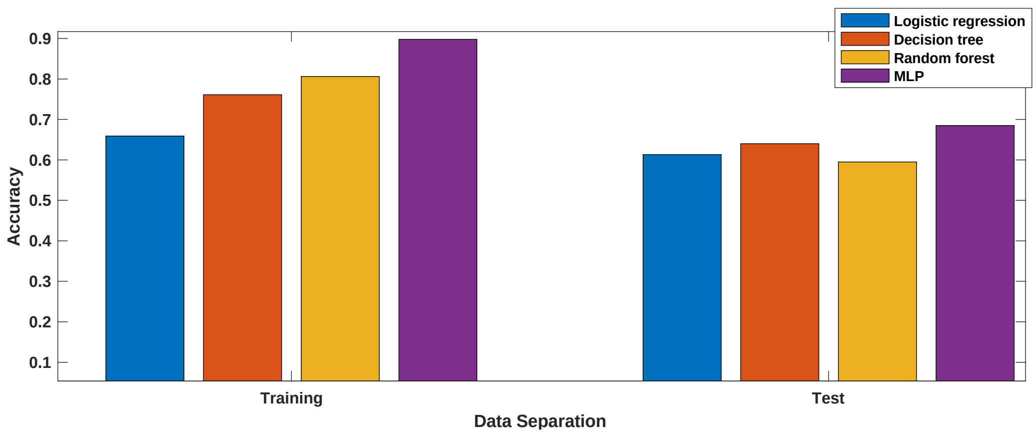


Fig. 6.1. Level of the Accuracy for Different Algorithms

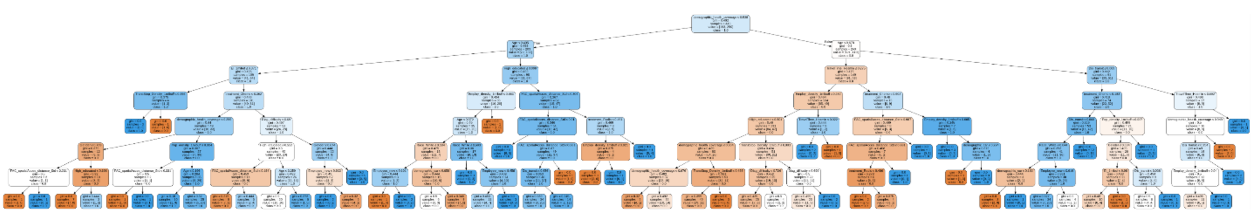


Fig. 6.2 Classifying the Determinant Attributes of QoL by Decision Tree Algorithms

In addition, the F score of each model is summarized in the Table 6.3 It is noteworthy that the MLP achieves the best F-score, i.e., 0.72. The rest three models, i.e., logistic regression, decision tree, and random forest achieve 0.70 F-score. This indicates that all the models are quite robust in predicting the positive class. In other words, our features are sensitive to characterize patients with high QoL.

Table 6.3. Performance Results for Various Algorithms

	Logistic regression	Decision tree	Random forest	MLP
F-score	0.70	0.70	0.70	0.72

To gain insight into the usefulness of each feature, we computed the importance scores related to each feature considering the random forest approach. We omitted features with small scores and only consider the most determinants of QoL (such as income, household size, perceived built environment). Table 6.4 indicates the top 18 features regarding the scores. The score is calculated as node impurity weighted by the probability of reaching that node and is normalized into [0,1]. Moreover, to understand the relationship intensity and direction of independent variables and QoL, Tables 6.5 summaries the results from logistic regression and describes the most significant determinants of QoL in cancer patients. The results from logistic regression support the decision tree algorithms. Comparing Table 6.4 and Table 6.5 indicate that the top 10 features selected by random forest are with lager coefficients in the logistic regression model. However, the results form the decision tree effectively follow the scores of random forest and are relatively in line with the coefficients from the logistic model (see Fig. 6.2). The age, health insurance, education, travel distance to the closest large hospital, perceived accessibility, and population density are among the most predictors of cancer patients' QoL in both decision tree and random forest scores.

Table 6.4. The Most Important Features Based on the Random Forest

	Feature Name	Importance Score
1	Age	0.14198
2	Travel distance to closest large hospital	0.12031
3	Perceived accessibility	0.11206
4	Distance to transit (min)	0.10921
5	Population density	0.09243
6	Health insurance	0.08123
7	Entropy index	0.07142
8	Education (Well-educated)	0.03246
10	Number of cars in the household	0.02834
11	Transit stop density	0.02341
12	Cancer treatments (*Chemotherapy)*	0.02240
13	Employment status (Employee)	0.01907
14	Cancer type (diagnosis)	0.01650

15	Gender	0.01106
16	Cancer treatments (*Radiotherapy)*	0.00730
17	Race (White)	0.00659
18	Cancer treatments (*Other)*	0.00292

Table 6.5. Coefficient for Each Feature in the Logistic Regression Model

Variables	Coef	St. Error	Z	P Values
Socio-demographic attributes				
Gender (Female)	0.2621	0.230	1.141	0.254
Race (White)	-0.0448	0.315	-0.142	0.887
Education (Well-educated)	0.6215	00.213	2.922	0.003***
Employment status (Employee)	0.2489	0.231	1.078	0.281
Number of cars in the household	0.2589	0.394	0.657	0.511
Health insurance	-0.7557	0.381	-1.984	0.047***
Age	1.8632	0.523	3.565	0.000***
Built environment characteristics				
Population density	-14.1817	7.153	-1.983	0.047***
Entropy index	-0.2651	0.629	-0.421	0.673
Transit stop density	-0.4187	0.706	-0.593	0.553
Distance to transit (min)	-2.2074	1.367	-1. 614	0.106
Travel distance to closest large hospital	1.6386	1.127	1.453	0.146
Perceptions				
Perceived accessibility	-1.1933	0.774	-1.543	0.123
Health-related variables				
Cancer type (diagnosis)	0.1053	0.308	0.342	0.732
Cancer treatments (*Radiotherapy)*	0.0180	0.251	0.072	0.943
Cancer treatments (*Chemotherapy)*	-0.7943	0.263	-3.021	0.003***
Cancer treatments (*Other)*	-0.3485	0.299	-1.164	0.244

6.5. Discussion

This study employs a cross-section survey to investigate how built environment impacts the Quality of life (QoL) of cancer patients.

The random forest’s results demonstrate the top ten most important features that predict the QoL of cancer patients (Table 6.4) and the logistic regression indicate the associations. Our results demonstrate that the built environment characteristics considerably contribute to predicting the QoL of the participants. According to the scored features in random forest, the travel distance to the closest hospital is one of the most significant predictors of QoL. Previous studies suggest that distance from residential neighborhoods to patients' treating hospital influence cancer outcomes, and consequently, those who reside far from their care provides may have lower QoL among cancer survivors (Thomas et al. 2015). Although travel distance to health facilities can be a barrier for cancer patients (Spees et al. 2019; Silver, Blustein, and Weitzman 2012; Salloum et al. 2012; Zullig et al. 2012) , this study considers the distance to the closest hospital and not the treated hospital. So, residing far from the large hospital can be an indicator of living in the low-dense suburbs.

The perceived accessibility is the third predictor of the QoL in random forest (Gao, Ahern, and Koshland 2016). The Perception towards accessibility to the neighborhood local services such as access to schools, public transportation, medical care, and shopping exhibits a significant effect on self-rated health (Wen, Hawkley, and Cacioppo 2006). Although the logistic regression does not indicate a significant association between the perceived accessibility and QoL, it seems that patients residing with less accessibility (greater values of perceived accessibility), reported lower level of QoL.

Distance to transit is the fourth important feature in the random forest. These measures are defined as the supportive built environment features that significantly can predict the QoL (Engel et al. 2016). The literature introduces the distance to transit and residential density as two of the objective indicators measuring the quality of urban life (Marans 2015). According to logistic model, patients residing in areas with more distance to transit declare lower QoL. The association is not statistically significant, but the direction is aligned with the theory.

Population density are other determinant of QoL in the random forest. Despite the lack of a clear understanding of the mechanism under which different urban density influence the QOL, some studies suggest that high density positively effects on increasing life satisfaction (Cao 2016). Higher population density can be positively associated with subjective well-being when accompanied by mixed land uses, public transport, limited car traffic, access to green spaces, and social equity (Mouratidis 2019). People reside in higher density neighborhood are more likely to perform physical activities (R. Ewing et al. 2003) and more possible to experience better health condition and life satisfaction (Stevenson et al. 2016). On the other hand, some research suggests that living in less dense areas can increase the quality of life while controlling for all the other sociodemographic and somatic health variables (Cramer, Torgersen, and Kringlen 2004). Accordingly, urban density contributes to QoL in different ways. The results of logistic regression in terms of density and QoL associations indicate an evident paradox. The earlier studies have often reported a positive relationship between population density and health outcomes due to the availability of walkable destinations, more tendency towards walking, biking, or public transit

(Ngom et al. 2016; Glazier et al. 2014). In contrast, our results suggest that a higher level of QoL is reported by the participants in neighborhoods with lower population density. Research on compact city form state that the negative association between life satisfaction and urban density stems from the emotional response of the residents toward perceived crime and stress in crowded and noisy neighborhoods (Mouratidis 2019). In contrast, residing in low-dense suburbs has positive effects on the well-being of the individuals through positive emotions and calmness (Carrus et al. 2015). In addition, higher levels of anxiety can be found in high-density areas and consequently decrease mental health (Lederbogen et al. 2011). The positive effects of density on well-being occur when it brings with mixed land use, access to public transit, restricted car travel, access to green spaces, and social equity (Mouratidis 2019). Accordingly, the adverse effects of population density on the self-reported QoL in cancer patients can be a result of their negative emotions towards the negative aspects of the density, such as traffic congestion, sense of crime and lack of green space.

The scored features of random forest reveal that the entropy index plays a moderate role in defining the level of self-reported QoL in cancer patients. Neighborhoods with mixed land use provide the cancer survivors accessibility to different errands in a walkable distance (Conroy et al. 2017). This result is in accordance with some previous studies about the compact city form in which state mixed land use has the potential to provide a better quality of life through offering longer, healthier and safer lives and contribute to the economic well-being and health of cities (R. H. Ewing and Hamidi 2014).

Random forest scores show that among all sociodemographic characteristics, respondents' age has an enormous contribution to the level of QoL among cancer patients. It seems that the process of aging in cancer patients can influence disease adjustment and therefore impact the health-related QoL (Bantema-Joppe et al. 2015). Our results from the regression model reveal that older cancer patients have a higher level of QoL. This finding is in line with the similar studies suggest that younger patients feel worse than older adults on some quality of life dimensions because they suffer more from psychological symptoms and financial issues (Arndt et al. 2004; Champion et al. 2014).

The random forest score of health insurance shows that this feature can differentiate the QoL experience through different levels. This result is in line with the previous studies that demonstrate health insurance status is associated with health-related of cancer patients over time (Penson et al.

2001), since patients with poorer insurance coverage may have less access to high-quality treatment, that resulted in later diagnosis and worse outcomes (Conlisk et al. 1999). This result confirms empirical evidence shows that health insurance can reinforce the health of vulnerable groups, such as senior adults, children, and people with premedical conditions and low-income populations (Pan, Lei, and Liu 2016). Moreover, the associations between health insurance and QoL explain that participants who have private and or employer-paid insurance health insurance reported a higher QoL level compared with low-income participants who have government-related insurance. It confirms the previous studies that offer cancer-related financial burdens related to increased risk of depression and lower health-related QoL in cancer patients (Kale and Carroll 2016).

The number of cars is the family is the tenth significant factor in predicting the QoL that has been identified by random forest. According to the best of our knowledge, there is no evidence to identify the effect of vehicle ownership on the QoL in cancer patients. However, vehicle is the most usual mobility mode particularly for residents of distant and rural areas, so, it can affect the cancer patients' access to treatment facilities while they might not have access to other mobility modes (Spees et al. 2019; Silver, Blustein, and Weitzman 2012; Arcury et al. 2005; Pucher and Renne 2005). Access to private vehicles and the option of driving with others are among the most crucial treatment-related factors that impose barriers to cancer patients (Guidry et al. 1997). Vehicle availability assumed as a variable that has a positive relationship with the early diagnosis stage (Parsons and Askland 2007), and receiving the first line of treatments (Salloum et al. 2012). Patients residing in areas having no access to a private vehicle are less likely to follow cancer screening treatments (Coughlin and King 2010). his evidence can support the contribution of access to a car in the QoL of cancer patients.

Furthermore, education is another factor contributing to the QoL of cancer patients. This result supports the studies that propose education improves well-being because it develops access to economic devices, enhances the sense of control over life, and increases social support (Ross and Willigen 1997). The positive association between education and QoL in this study can be justified the earlier research suggesting that low education along with low neighborhood socioeconomic status result in worse all-kind survival for particular cancers (Shariff-Marco et al. 2017).

The higher score related to the significance of chemotherapy compared with radiotherapy reveal that chemotherapy treatment has a more significant contribution in predicting quality of life

(Berglund et al. 1991). Chemotherapy treatment appears to have a negative effect on the QoL of those patients who received this treatment. Although physicians suggest chemotherapy to improve QoL for patients with end-stage cancer, it cannot reinforce QoL for patients with moderate or poor performance status and worsened QoL close for patients with good performance status (Prigerson et al. 2015). Gender and race have a small participation in determining the level of QoL. The race of the participants (white versus other races) has a small but notable effect on QoL after treatment (Morrow et al. 2014).

Chapter VII: Conclusions and Recommendations

7.1. Transportation Accessibility and Cancer Outcomes

According to our study findings, travel distance to health care facilities cannot consistently expectedly predict the receipt of treatment. Although travel distance reduces the accessibility of patients to care services, our findings suggest that participants who decide to travel longer distances to radiotherapy centers have greater tumor-free years due to access to higher quality health care.

However, travel distance would still be a barrier for those who live in distant areas such as rural settings. Further research and work will be required to characterized the quality of radiotherapy provided when patients travelling further distances and to quantify the travel cost-benefits for patients (White et al. 2017). Accordingly, the priority should be given to planning for 1- Strengthening strategies to refer cancer patients to high-quality regional health centers for treatment efficiently, 2- Decreasing transportation burdens by providing access to health facilities, and 3- reducing referral patterns that can contribute to disparities in access to high-quality cancer care by different income groups, ethnicities, and races (Macleod et al. 2018).

On the other hand, early stage of cancer patients residing in urban settings find travel distance as a greater burden comparing with those patients residing in rural areas due to the diversity of their transportation accessibility (Spees et al. 2019). It has been explained that residents of rural and distant areas are more dependent to their private transportation and accustomed to travelling long to receive facilities. So, they are more probable to travel long distances to follow cancer treatments. However, urban residents have more transportation options; are more public transit dependent, and are more likely to decide not travelling far distances if they experience the travel to treatment as a burden (Probst et al. 2007; Arcury et al. 2005). Therefore, to improve the level of access to health facilities, policies, and strategies should be tailored to different geographical regions, including rural and urban settings.

Moreover, this study found that among cancer patients, distance to care was only associated with radiotherapy treatment. It seems that chemotherapy are less susceptible to travel barriers in the cancer population (Spees et al. 2019). Chemotherapy services may be placed closer to less urbanized locations, thereby lessening the influence of distance on these types of treatment.

This fact that cancer patients travel longer distances to treatment have improved cancer outcomes, emphasize the need of expanding the supportive transportation programs and services. For instance, the American Cancer Society "Road to Recovery" program provides transportation to and from treatment for patients who do not have a ride or are unable to drive themselves. According to statistics, this service provided approximately 490,000 free rides to treatment for cancer patients in 2019. This program also provide patients with transportation cost ($50) to treatment for those patients who don't have a ride or are unable to drive themselves (Sams 2019).

Expanding the similar supportive programs which provide free rides to patients with lack of access to private vehicle, can be an effective, low-cost strategy to increase access to cancer care particularly for low-income population.

7.2. Transportation Accessibility and Cancer Decision-making

Since cancer patients require to follow a treatment schedule with frequent and several visits (American Cancer Society 2020a; National Cancer Institute 2015a), one of the most significant issues that they confront is accessing to affordable transportation to make their treatment appointments. On the other hand, the cancer patients' ability to drive can be affected by treatment's side effects (Zullig et al. 2012), and therefore impact cancer patient's accessibility to treatment centers. Thus, transportation can potentially become a barrier in terms of pursuing treatment for cancer patients and consequently will affect health outcomes. Our results suggest that lack of access to transportation is among the most significant factors that affect cancer patients' decision-making regarding continuing/stopping their treatment.

While the previous transportation policies aimed to improve travel convenience and roadway expansion, the newer ones are mostly trying to enhance people's accessibility options rather than their mobility options (Litman 2013). Therefore, to improve public health and enhance cancer patients' opportunities for better access to treatment, it is fundamental to implement policies and strategies concentrating on the diverse transportation system. It can be achieved by providing cancer patients with more mobility options to travel to health facilities, including public transit and shared mobility. Besides, transportation barriers in terms of access to health and medical services have higher significance when it comes to minorities and vulnerable populations (Wallace et al.

2005). Therefore, it is essential to consider the most affordable transportation options to be available for this population. Since our results indicate that the majority of participants use the private vehicle as their principal mode to access to treatment facilities, future interventions should consider more available, convenient and affordable car trips through supporting ride-sharing programs in addition to public transit discounts and medical transportation services. Moreover, the accessibility to health services could be limited when people are only dependent on private vehicle, and it mainly affects those who are physically, economically, and socially disadvantaged (APTA 2010; Litman 2012). High-quality public transit increases people's access to health-related goods and services, particularly for minorities and disadvantaged groups. On the other hand, many public transit dependent patients are more probable to miss appointments or have late arrivals compared to those who have used cars as their primary mode of transportation (Wallace et al. 2005; Rask et al. 1994). Accordingly, adding to the existing routes, increasing operating hours, and providing more frequent services (Litman 2013) are among the policies that public transit service could apply to improve patients' accessibility to treatment and care.

Our results emphasize the need for collaboration between health policy makers, urban planners and transportation experts to conduct more research regarding the effects of transportation policies on health outcomes. Some public health policies, such as reimbursement of healthcare transportation payments, can encourage patients to keep their appointments and avoid stopping their treatments. Furthermore, mor research should be conducted about the effects of new technological innovations on patients' access to health care. Autonomous vehicles (AVs) services that offer free shared-rides to patients is an example of innovation transportation programs that can improve the health care accessibility.

7.3. Cancer and Quality of Life

Cancer statistics indicates that the number of people diagnosed with cancer in the United States will rise to approximately 1.8 million individuals in 2020 (American Cancer Society. 2020). Accordingly, urban design and transportation planning require to become more friendly for this population group with particular needs and requirements. Evidence indicate that physical interventions influence on improved QoL of cancer patients (Duncan et al. 2017). Reviewing the literature indicate that performing physical activity such as walking and exercise interventions may significantly result in a higher quality of life for patients with cancer history (Oh et al. 2018; Mishra et al. 2012; Ho et al. 2019; Gopalakrishna et al. 2017). Accordingly, supportive built environment can overcome the barriers in the outdoor environment, increase the likelihood of having physical activity, and therefore improve the perceived quality of life (Rantakokko et al. 2010; Engel et al. 2016). The results from our study suggest that living environment and mobility related factors such as travel distance to the closest large hospital, perceived accessibility, distance to transit, and population density are among the most significant predictors of the cancer patients' QoL. Built environment features in terms of land use patterns, urban design features, and transportation systems are recognized as important determinants of chronic health conditions such as cancer (McCormack et al. 2019). These findings reveal that to improve social equity; it is fundamental to design environments compatible with the needs of all community groups, including people who are struggling with chronic diseases that require ongoing medical attention or limit activities of daily living in long term. Understanding the associations between the built environment and health-related QoL can develop intervention policies that aim to improve cancer patients' well-being.

Hence, we need a collaboration of transit agencies, MPOs, and community planning to target the living environment and mobility needs of people who are burdening with chronic disease. To this end, urban and transportation planners and practitioners require to be involved in this field more and acquire more knowledge from other disciplines. Integrating transportation planning with public health and social studies could improve the existing policies and strategies the transportation accessibility and equity and therefore increase the well-being and QoL.

In this study, we employed the self-reported QoL and identified the most significant factors contributing to improved QoL. However, there is an inherent need to develop a QoL measurement that comprehensively counts for subjective feelings as well as objective factors in terms of patients' health condition, transportation, and built environment. This QoL measurement can be used as a policy tool by communities and local governments to evaluate the extent to which the mobility and built environment meet patients' needs with chronic disease.

Furthermore, our findings suggest that population density are among the most predictors that inversely affect the cancer patients' QoL. Although previous studies offer that high density positively effects on increasing life satisfaction (Cao 2016), this relationship can be occurred when accompanied by mixed land uses, access to public transit, limited car traffic, access to green spaces, and social equity (Mouratidis 2019). Compact development strategies can be fulfilled when policymakers address the side effects of urban density, such as fear of crime, high noise, and traffic congestion. This compact development pattern should concentrate on strategies that increase robust transportation options and improve public health indicators such as air quality while creating safe and secure neighborhoods that preserve more open space.

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Appendix A:

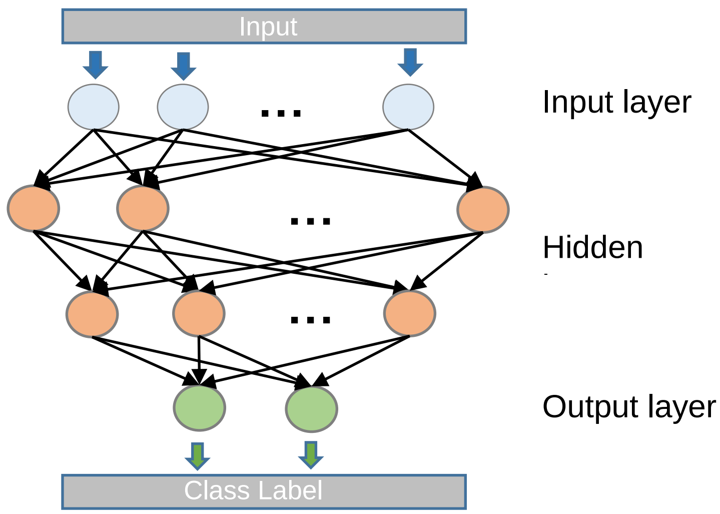

Fig. A.1. Layers in a Typical ANN Model

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