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Impact of Coronavirus Disease 2019 on Secondary Market Ticket Price, Attendance Demand, And Fan's Willingness to Pay: National Football League (NFL)

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IMPACT OF CORONAVIRUS DISEASE 2019 ON SECONDARY MARKET TICKET PRICE, ATTENDANCE DEMAND, AND FAN'S WILLINGNESS TO PAY: NATIONAL FOOTBALL LEAGUE (NFL)

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has been approved as meeting the requirement for the Degree of Doctor of Philosophy in the Department of Kinesiology, Nutrition, and Dietetics, in the College of Natural and Health Sciences, Program of Sport Administration.

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ABSTRACT

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This study explores how coronavirus disease 2019 (COVID-19) affected secondary market ticket prices, the number of attendees, and fans' willingness to pay in the National Football League (NFL). The COVID-19 pandemic has significantly impacted the sport industry, affecting everything from the scheduling and delivery of games to the financial health of teams, leagues, and related businesses. One of the most visible impacts of the pandemic has been the suspension, delay, and cancellation of many sporting events, including entire seasons of some professional sport leagues. Sporting events require large gatherings of people in close proximity, which is precisely the opposite of what is needed to control the spread of the virus. The pandemic has also led to the closure of sports venues, training facilities, and other sports-related businesses, leading to significant financial losses. In addition to the postponement or cancellation of events, the pandemic has also affected how sporting events were disclosed to fans. Many events were held without fans in attendance or with limited-capacity crowds. Therefore, amid disease threats, examining the secondary ticket market, attendance demand, and willingness to pay is important: fan demand and willingness to pay concerning updated marketing and ticket pricing policies can influence revenue generation in sport.

Two types of data observations were collected for this study: primary and secondary. Specifically, secondary market ticket prices and the number of attendees for each game were collected during NFL 2022 season to investigate the impact of COVID-19 health risks on ticket prices and attendance demand. Also, the survey was designed to understand NFL fans' willingness to pay for tickets amid the pandemic. A multilevel regression model analysis was adopted due to the nested structure of the data, involving secondary data such as ticket prices and the number of attendees. Also, structural equation modeling analysis was utilized to investigate NFL fans' willingness to pay. The results show that when secondary market sellers' ticket prices significantly reflected COVID-19 deaths, NFL fans considered COVID-19 cases whether they attended a game or not. Also, team performance predictors are a significant consideration for price and attendance demand determinations. Although the risk attitude of COVID-19 directly explained fans' willingness to pay (WTP) for additional safety in the stadium, willingness to pay for a ticket does not have a significant relationship with willingness to pay for higher safety measures. However, WTP was significantly related to past spending on NFL game tickets. Overall, this study found that COVID-19 health risks (i.e., COVID-19 cases and deaths) explain ticket prices in the secondary market and the number of attendees in the NFL. Also, the results uncovered fans' willingness to pay for higher safety services amid the pandemic that is related to the COVID-19 surcharge.

Keywords: secondary ticket market price, attendance demand, willingness to pay, COVID-19, National Football League

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CHAPTER I

INTRODUCTION

An Introduction to Ticket Pricing in the Sport Industry

This dissertation theoretically and empirically examined several aspects of secondary market ticket pricing, attendance demand, and consumers' willingness to pay in the sport industry amid the pandemic. Pricing has been studied in the general business industry for several decades, with the topic being considered a key marketing element (Borden, 1964; Robicheaux, 1976). As LaPlaca (1997) and Shipley and Jobber (2001) indicated, pricing represents organizations' sole means of generating revenue in accordance with traditional marketing. Pricing is a differentiating factor among competitors (Shipley & Jobber, 2001) and serves as an initial consumer touchpoint; pricing strategies foster business success alongside marketing (Gijsbrechts, 1993; Schindler & Schindler, 2011). Udell's (1964) work regarding the importance of pricing in business highlighted this task as one of five integral marketing strategies. Given the topic's importance, research on pricing in consumer goods has expanded over time based on market needs and consumer sensitivity (Chen & Iyer, 2002).

The sport industry researchers started to turn their attentions to ticket pricing after investigating similar industries, such as leisure, entertainment, airlines, and hotels. Understanding ticket pricing is crucial for two main reasons. Firstly, pricing strategy is a crucial revenue management tactic in the sport industry, as ticket sales make up a significant proportion of revenue for sport organizations, along with broadcasting rights, stadium naming rights, sponsorships, and merchandise sales (Dees et al., 2021; Drayer et al., 2012b). In 2010, ticket sales generated around $20 billion in revenue for sport organizations, according to Wanless and Judge (2014). In other words, for most professional sport organizations and collegiate athletic departments, ticket pricing is their primary source of revenue generation (Smith & Roy, 2011). Secondly, there is a strong correlation between ticket pricing and consumer demand. As Boyd and Boyd (1998) pointed out, when ticket prices are lowered, there is an increase in the number of attendees at stadiums. Another example is that high demand leads to higher ticket prices in the sport industry (Drayer et al., 2012b). Therefore, it is crucial for sport organizations to carefully consider their ticket pricing strategies to maximize their revenue and optimize attendance.

Development of Demand-Based Ticket Pricing

From the late 1990s to the early 2000s, the sport industry started to receive significant academic attention regarding ticket sales and prices. Initially, the focus was on fixed pricing in the primary market, where professional sport organizations act as sellers. For many years, using fixed pricing, professional teams relied on uniform pricing and seat locations as their primary revenue management method in the primary market. Under this strategy, sport teams maintain consistent ticket prices for entire game seasons until they adjust prices for the upcoming season (Drayer et al., 2008, 2012b). As a result, sport fans pay the same prices for specific games, regardless of the game's appeal. Therefore, early studies focused on identifying factors influencing ticket pricing decisions each year and why prices changed per season across teams in multiple sport leagues.

Although sport organizations initially believed that fixed ticket pricing was the best way to maximize revenue, they were unsatisfied with the number of attendees. Burton and Cornilles (1998) pointed out that empty stadium seats were a significant concern for both professional and collegiate sport organizations because attendance directly impacts gate revenue through ticket sales. Nowadays, sport fans have many options for following games, such as watching them on television, streaming online, or listening to them on the radio. They also have various choices for entertainment, including different sport events.

To address concerns about increasing attendance demand, sport organizations began to adopt demand-based ticket pricing, which includes variable ticket pricing (VTP) and dynamic ticket pricing (DTP). The Colorado Rockies was the first to implement VTP, and the San Francisco Giants began to explore DTP as primary ticket pricing strategy. Other industries have also used this approach as a revenue management strategy. For example, airlines use DTP, such as offering early-bird fares (McGill & van Ryzin, 1999), because empty seats on flights significantly affect their revenue. Similarly, sport event tickets are also perishable, meaning unsold tickets cannot be used, listed, or updated in the market once a game starts. Therefore, based on the success of demand-based pricing in related industries, sport organizations began considering VTP and DTP as essential methods to sell more tickets, meaning greater stadium attendance.

Secondary Ticket Market in the Sport Industry

The secondary ticket market has generally been defined as a resale market. In the sport industry, this market is a platform where ticket holders resell sport event-related tickets for lower or higher prices after buying from the primary ticket market, which sport organizations manage. The primary ticket market is where tickets are initially sold by authorized sources at face value through official ticketing companies or vendors. Prices in the primary market are stable and predictable, with a lower risk of encountering counterfeit tickets. On the other hand, the secondary ticket market involves the resale of tickets purchased from the primary market. Prices in the secondary market fluctuate based on supply and demand, and they can be higher or lower than the original face value. Tickets in the secondary market are available from individual sellers or resale platforms, but there has been a higher risk of encountering fraudulent or counterfeit tickets (Drayer & Martin, 2010). The secondary market also offers greater ticket availability, including the opportunity for last-minute purchases. The secondary market takes various forms in the sport industry: person-to-person sales (e.g., purchasing tickets from acquaintances), scalping (e.g., selling tickets above face value), and website-based market venues (e.g., StubHub and eBay). According to Drayer and Martin (2010), the secondary ticket market in sport was at first suspected of being illegitimate due to immoral behavior such as ticket fraud and price gouging. For instance, scalpers take advantage of sport fans for profit (Smith, 2009). Professional sport organizations, as primary sellers, have struggled to manage ethical issues in the secondary market.

After secondary ticket market platforms fought to gain legitimacy from the public and sport fans in past decades, web-based ticket resale platforms have striven to rehabilitate this market’s image. Sponsorships between secondary ticket market platforms and professional sport organizations represent one strategy (Dees et al., 2021; Drayer & Martin, 2010). For example, Major League Baseball (MLB) established a partnership with StubHub, and the National Football League (NFL) partnered with SeatGeek. Web-based market venues now embody the most efficient platforms for resellers and consumers: “Web-based ticketing–applying internet technology to selling and/or reselling tickets–is a prominent component of ticket operations” (Howard & Crompton, 2004, p. 92). Thanks in part to technological developments and sponsorships that have raised legitimacy, the secondary ticket market in sport has ballooned into a multi-billion-dollar industry. There are over 1,000 official ticket brokers and roughly 800 web-based platforms in the United States alone (Happel & Jennings, 2002; Shapiro & Drayer, 2014).

This market is also lucrative: eBay sold StubHub to Viagogo, one of the largest web-based secondary ticket market platforms, for over $4 billion in 2020 (Sisario, 2019).

For several reasons, the secondary ticket market has captured the interest of resellers, consumers, and professional sport organizations. First, secondary market sellers—mostly season ticket holders (resellers)—can adjust ticket prices without restricting profit based on consumer demand. Conversely, primary market prices were constrained by seat location, event quality (Shapiro & Drayer, 2014), and other factors (Reese & Mittelstaedt, 2001; Rishe & Mondello, 2003, 2004) before DTP pervaded the primary market. In terms of ticket pricing, the secondary market is fully demand-driven. In other words, resellers determine ticket prices based on the level of consumer demand for each event without having a price ceiling and floor (Shapiro & Drayer, 2012). Resellers can raise prices above face value (i.e., sport organizations' prices in the primary ticket market) for high-demand games; lower-demand games command lower prices. Purchase choices constitute another reason for the secondary market's popularity. Market sellers offer consumers event seats and flexible options (Shapiro & Drayer, 2014) for specific games at reasonable prices based on attendees' values (Drayer & Shapiro, 2009; Drayer et al., 2012b). Potential buyers have numerous ticket options based on their event expectations.

In addition, the secondary market provides sellers, especially season ticket holders, the opportunity to avoid losing money by selling tickets to events they cannot or wish not to attend. Buyers who might otherwise be unable to afford high-level tickets or the fixed primary market price for an event then have a chance to purchase tickets below face value (Lewis et al., 2019). The secondary market also enables resellers to maximize profit. When analyzing a collection of San Francisco Giants tickets, Shapiro and Drayer (2012) stated that the median secondary market ticket prices were 42% higher than dynamically priced tickets on the team's website. In other words, average transaction prices in the secondary market tend to exceed those in the primary market.

Importance of Attendance Demand

The number of attendees is one of the most crucial factors in the success of sport organizations. Attendance demand directly impacts the financial performance of teams, leagues, and venues (Coates & Humphreys, 2007; Hall et al., 2010). For example, ticket sales, concessions, merchandise sales, and other game-day revenue streams depend on the number of fans attending games (Coates & Humphreys, 2007). High attendance numbers can translate into significant revenue for sport organizations, while low attendance numbers can result in financial losses. Attendance demand also represents the level of engagement and interest that fans have in a particular sport or team (e.g., Stander & De Beer, 2016). High number of attendees suggests a solid and engaged fan base, while low attendance may indicate a waning interest in the sport or team. Therefore, attendance demand is essential in helping sport organizations to make informed decisions about their marketing, pricing, and other operational strategies to optimize their revenue and fan engagement.

Furthermore, the presence of a large and enthusiastic crowd can significantly impact the atmosphere and overall experience of attending a sports event (e.g., Wann, 1995). A complete and energetic stadium can create an exciting and memorable experience for fans, players, and other stakeholders (Wakefield & Bennett, 2018). Conversely, a lack of attendance can result in a lackluster atmosphere, impacting the overall experience for all involved. Positive in-stadium experiences highlight the importance of attendance demand in creating a vibrant and engaging environment that enhances the overall experience of attending a sporting event. Attendance demand also can impact the value of sponsorship and advertising deals for sport organizations

(Biscaia, 2015). Sponsors and advertisers may be more likely to invest in sport organizations with high attendance numbers and a strong fan base. More sponsorship involvement can provide additional revenue streams for teams and leagues and enable them to invest more in their operations and player development.

Lastly, sport organizations and resellers also consider attendance demand in their pricing determinations, as discussed with demand-based ticket pricing strategies. Attendance demand significantly impacts ticket pricing strategy in sport (Coates & Humphreys, 2007). Sport organizations must set ticket prices that will attract fans while maximizing revenue. Fan attraction requires a careful balance between pricing the tickets appropriately to cover costs and generate revenue while ensuring that the prices are affordable enough to attract a large number of fans. Generally, when attendance demand is high, sport organizations can charge higher ticket prices (Shapiro & Drayer, 2014). For example, when a team performs well and is likely to make it to the playoffs or championship, fans are more likely to attend games, and the organization can increase ticket prices. Conversely, when attendance demand is low, sport organizations may need to lower ticket prices to attract fans and fill seats. Attendance demand is critical to the success of sport teams and leagues as it impacts their financial performance, fan engagement, atmosphere, experience, and sponsorship and advertising deals. As such, sport organizations must continuously monitor and understand their attendance demand to make informed decisions about their marketing, pricing, and other operational strategies to optimize their revenue and fan engagement.

Consumer's Willingness to Pay

In relation to demand-driven ticket pricing and the expansion of the secondary ticket market, consumers' willingness to pay (WTP) has been considered another important topic in the sport industry. As mentioned, ticket pricing is one of the most effective revenue-generating tools in business concerning attendance demand (Han et al., 2001). Scholars have verified the roles of pricing strategies in consumers' purchase decisions, sales volume, and product positioning (Cressman, 2012; Gabor & Granger, 1966; Gijsbrechts, 1993). Therefore, to implement efficient pricing by understanding consumers, organizations in numerous industries (e.g., fashion, automobile, and sport) have explored factors that significantly influence consumer demand and WTP.

As sellers have reflected on consumers' desires and the extent to which people value products based on price, an important question has emerged: What are the highest prices customers are willing to pay for merchandise? As Le Gall-Ely (2009) described, WTP captures "the maximum price a given consumer accepts to pay for a product or service [. This concept] is of particular interest as it is richer in individual information" (p. 92). When a product's market price is determined based on the price ranges consumers are willing to pay, a significant difference can manifest between organizations' pricing strategies and WTP. For example, the lowest asking price for tickets to Super Bowl LVI (Cincinnati Bengals vs. Los Angeles Rams) was about $4,300 per seat. This cost was informed by several factors affecting consumer demand in the NFL ticket market. However, sellers could not know exactly how much potential attendees were willing to pay for tickets. Fans of the Bengals or Rams who earned a high income would presumably pay more than the listed price to support their team at the Super Bowl—yet even with similar demand to attend the game, the WTP of fans earning a moderate or low income would be far below sellers' asking prices.

Statement of the Problem

The secondary ticket market is demand-driven and related to attendance demand, and consumers' WTP is significantly related to demand as well as perceived product/service value. Secondary market ticket pricing, the number of attendees, and consumers' WTP thus remain core considerations. Given that consumer demand significantly and directly affects revenue generation, researchers have continued to uncover attributes influencing secondary market ticket pricing and associated attendance demand. Salient characteristics include team quality (i.e., home and away team performance), the presence of star players, weather (e.g., forecasted temperature and precipitation rate), day of a game (e.g., weekday vs. weekend), population, and income per capita (e.g., Drayer & Shapiro, 2009; Drayer et al., 2012b; Sanford & Scott, 2016; Shapiro & Drayer, 2014; Shapiro et al., 2021).

While multiple price and attendance determinants affecting sport consumers' WTP have been investigated, consistent research is required amid circumstances such as economic crises, threats of terrorism, and war. Especially, little is known about how the coronavirus disease 2019 (COVID-19) pandemic has shaped secondary market ticket pricing, attendance demand, and sport fans' WTP. These phenomena should be explored because COVID-19 (a) is the first pandemic to touch sport industry actors in the United States and worldwide and (b) has raised economic concerns in diverse industries (Maital & Barzani, 2020) that have affected the economic standing of entire communities, including sport industry consumers.

SARS-CoV-2, which resulted in the COVID-19 pandemic, began to spread globally in late December 2019. The virus was not considered a severe situation at first. However, under a fast-growing threat, international experts and individuals began to be concerned about the illness. People who had already experienced disease-related outbreaks (e.g., swine flu, Hong Kong flu, and Spanish flu) were especially worried about this illness's health and economic consequences. Tufan and Kayaaslan (2020) claimed that the number of social media posts could convey individuals' degree of panic. Millions of photos and videos containing information (both accurate and misleading) about COVID-19 have been published as people seek updated information. COVID-19 is unpredictable; it has been impossible to prepare completely or to prevent the virus's spread entirely. The World Health Organization confirmed 595,219,966 cases and 6,453,458 deaths around the world as of September 19, 2022.

COVID-19 has threatened many business sectors, and the sport industry is no exception. Industry actors initially did not consider COVID-19 to be severe. Each league formulated different policies to respond to COVID-19 based on season status (i.e., in the middle, at the end of the season, or in the off-season). The NFL finished its scheduled games, including the playoffs, Super Bowl LIV, and pro bowl; National Basketball Association (NBA) games were played continuously in a bio-secure bubble without in-person attendance. Similar to sport leagues in the United States, major European sport leagues hosted games behind closed gates: in soccer, the Champions League and Europa League games were held without attendees.

The rapidly growing number of cases and deaths quickly led sport organizations in the United States to reconsider their policies to prevent or curb an outbreak as well. Games without spectators were not a viable solution; players, coaching staff, and other industry actors resided in risky environments. Even if sport organizations wished to continue hosting games in empty stadiums, there often were insufficient players and staff due to illness. Sport fans were unable to attend in person beginning in mid-to late March 2020. Events were also not televised; fans could not watch sports via streaming services for several months.

After a 6- to 12-month gap contingent on the league, corresponding to the development of vaccines, sport fans were again allowed to see games in person and to watch event broadcasts. Fans' experiences were drastically different compared with seasons prior to COVID-19. For example, most professional sport leagues in the United States announced new health and safety protocols. Venues were open at about 10%–30% of total capacity, depending on the stadium and local COVID-19 conditions. Professional teams, and some collegiate teams, controlled secondary market ticket sales to maintain social distancing (i.e., tickets were sold in groups or "pods" of two, four, or six in accordance with stadium policy). All attendees had to wear a mask while at the venue.

Sport fans and consumers were susceptible to economic difficulties as well. Millions of people lost their jobs globally due to COVID-19, leading to financial concerns (Crayne, 2020) that could affect consumers' purchases—especially of hedonic goods (e.g., movies, books, art, and sport products) and other nonessentials. Dhar and Wertenbroch (2000) described hedonic goods as those that "provide more experiential consumption, fun, pleasure, and excitement (designer clothes, sports cars, luxury watches, etc.), whereas utilitarian goods are primarily instrumental and functional (microwaves, minivans, personal computers, etc)" (p. 60). COVID-19 delayed business-related and personal economic activities for at least two years. The outbreak of COVID-19 caused a delay in economic activities for both businesses and individuals, which lasted for a minimum of two years. As a result of the pandemic's impact on global cases and deaths, the worldwide gross domestic product (GDP) was projected to decrease by 5.2% in 2020, compared to the pre-COVID-19 levels in 2019. However, the actual decrease in global GDP in 2020, compared to 2019, was 3.1%, according to the World Bank (2020).

Sport organizations also lacked proper ticket pricing and marketing strategies due to the absence of information about attendance demand and consumption in the pandemic era. Although some industry actors had likely experienced crises such as terrorism, COVID-19 was the first pandemic to sweep the globe. Terrorism can also be tied to scheduled sport events, whereas COVID-19 has consistently threatened daily life for an extended period. The circumstances of the pandemic forced sport organizations to lay off and dismiss employees. Given a paucity of suitable risk management strategies, these organizations could only partially recover their financial losses after reopening.

Research Questions and Hypotheses

This study analyzed COVID-19's impact on secondary market ticket pricing, the number of attendees, and the NFL fans' willingness to pay. Findings will help sport organizations and ticket market actors better understand ticket pricing strategies, attendance demand, and aspects influencing willingness to pay facilitate revenue management during the pandemic and similar crises. First, four research questions (Qs) guided investigation of ticket pricing and attendance demand:

Q1 After accounting for previous findings of price determinants, does number of COVID-19 cases explain NFL secondary market ticket price?

Q2 After accounting for previous findings of price determinants, does number of COVID-19 deaths explain NFL secondary market ticket price?

Q3 After accounting for previous findings of price determinants, does number of COVID-19 cases explain NFL in-stadium attendance demand?

Q4 After accounting for previous findings of price determinants, does number of COVID-19 deaths explain NFL in-stadium attendance demand?

To address the research questions, secondary data (i.e., secondary market ticket prices and the number of attendances) were collected. Specifically, the number of COVID-19 cases and deaths were also collected as key variables of interest. Moreover, around 20 control variables were collected based on past studies of price and attendance demand determinants.

Previous Findings of Ticket Price and Attendance Determinants

In the past decade, ticket pricing and attendance demand literature was developed with six major categories of price determinants (Shapiro & Drayer, 2014):

Time-related Variables. Part of season (i.e., early, mid, and late season); day of a game (i.e., weekday Vs. weekend); time of game; and days before the game.

Game-related Variables. Game day number/game week; division affiliation; league affiliation; special circumstances (e.g., promotions and giveaways); and national television broadcast

Environmental Variables. Temperature and precipitation forecasts

Team Performance Variables. Home team winning percentage; away team winning percentage; home team winning percentage in last 10 games; away team winning percentage in last 10 games; home team post season status in previous season; away team post season status in previous season.

Individual Performance Variables. Number of all-stars on home team's roster; number of all-stars on away team's roster.

Ticket-related Variables. Seat location (e.g., aisle seat); ticket availability; group ticket size.

With research questions of ticket pricing and attendance demand, additional two research questions guided investigation of consumer's willingness to pay amid pandemic era with seven hypotheses:

Q5 Do NFL fans' perceived threats of COVID-19 explain willingness to pay to attend sport events?

Q6 Do NFL fans' perceived threats of COVID-19 explain willingness to pay for additional safety measures in the stadium?

Hypotheses

The first hypothesis, listed below, investigates the impact of risk-taking on perceived risk based on the General Risk Propensity Scale (GRiPS) (Zhang et al., 2019). Specifically, this study explored the propensity for risk-taking as a possible predictor of willingness to pay during the presence of COVID-19 (see Figure 1.1).

H1 The higher one's level of risk taking, the lower the perceived risk from COVID-19.

This study also investigated the impact of perceived risk related to COVID-19 on perceived attitude and perceived behavioral control towards the virus and how this is linked to risk-taking tendencies. In particular, previous research has examined the impact of perceived risk and perceived behavioral control on consumer demand, behavior, and willingness to pay (e.g., Lepp & Gibson, 2003; Sánchez-Cañizares et al., 2021). Perceived risk refers to the degree to which NFL fans view COVID-19 as a significant risk factor. Perceived behavioral control measures their willingness, ability, and perceived level of control in participating in sporting events during the pandemic.

H2 The higher the perceived risk from COVID-19, the more negative one's attitude towards COVID-19.

H3 The higher the perceived risk from COVID-19, the lower one's perceived behavioral control over COVID-19.

Hypothesis 4 in this study aimed to investigate how perceived risk during the COVID-19 pandemic affects the willingness to pay among NFL fans. Hypothesis 5 examined the relationship between perceived behavioral control and willingness to pay. Furthermore, the study also considered the influence of previous purchase prices on willingness to pay, which was investigated in Hypothesis 6, based on previous research (Miller et al., 2011).

H4 The higher one's risk attitude from COVID-19, the lower their WTP to attend NFL games amid the pandemic.

H5 The higher one's perceived control behavior over sporting event participation, the higher their WTP to attend NFL games amid the pandemic.

H6 The higher one's spending on NFL tickets prior to COVID-19, the greater their WTP to attend NFL games amid the pandemic.

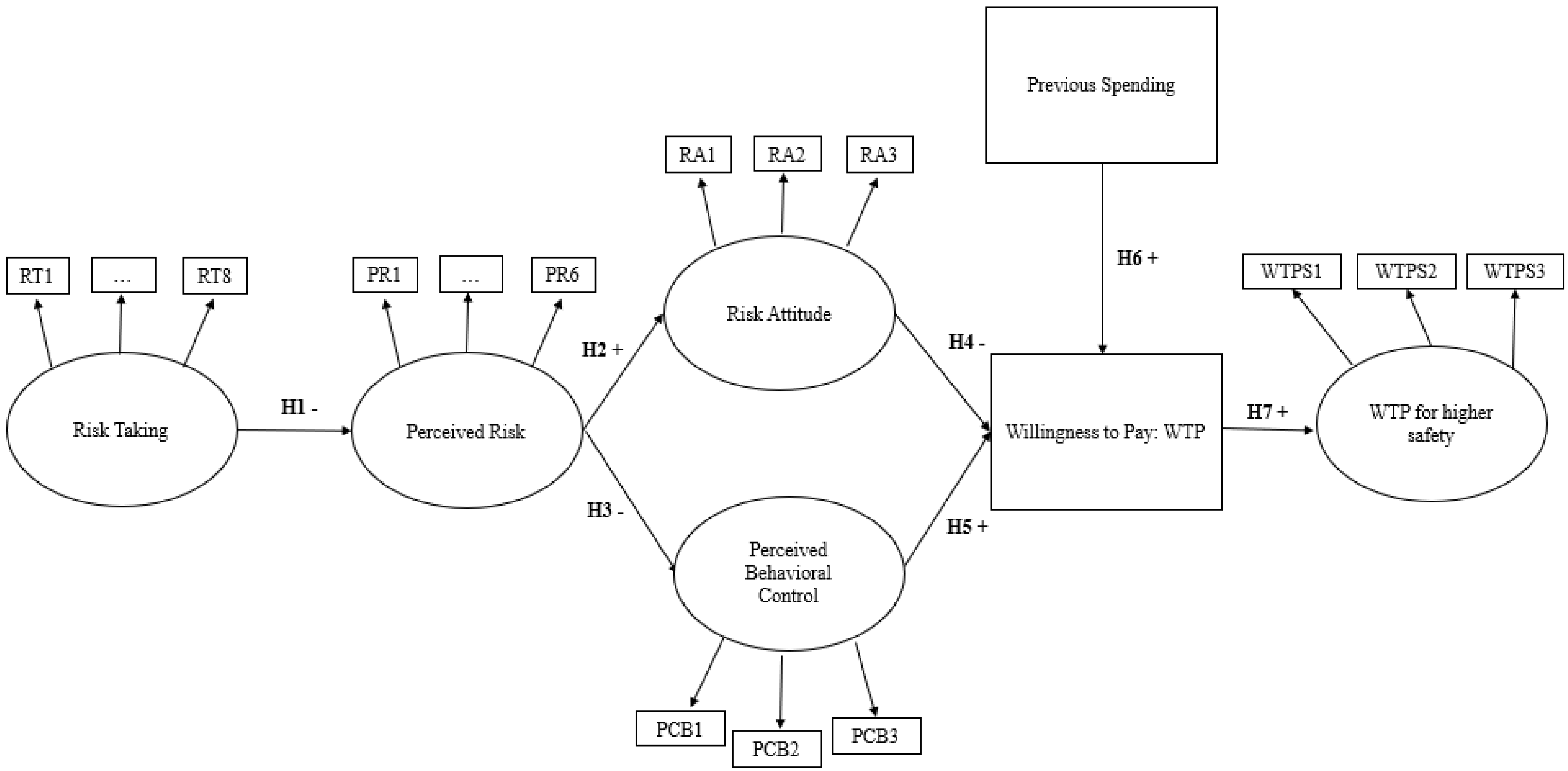
Finally, building on prior studies that link consumers' willingness to pay with their interests and demand (Miller et al., 2011), Hypothesis 7 investigated the relationship between the willingness to pay for NFL tickets and the willingness to pay for enhanced safety measures in stadiums aimed at mitigating the risks associated with COVID-19.

H7 The higher one's WTP to attend NFL games during the COVID-19 pandemic, the greater their WTP for better safety services.

The second data set involves survey data for research questions 5 and 6, which were analyzed using a structural equation model based on Hypotheses 1 through 7 (See Figure 1.1).

Figure 1.1

Theoretical Model for National Football League Fans' Willingness to Pay



Delimitation and Limitation

Prior to summarizing the chapter, the delimitations and limitations of this study should be understood. In research, discussing delimitations and limitations is essential to establish the study's scope, boundaries, and potential weaknesses. Delimitations refer to the constraints and choices made by the researcher during the study, such as sample size, variable selection, or research design. Limitations refer to factors that may impact the validity or reliability of the results, such as potential biases, generalizability, or measurement errors. By acknowledging delimitations and limitations, researchers can identify areas for future research, increase the transparency and credibility of their findings, and refine their research questions, hypotheses, and methodology. Discussing these aspects can also help readers evaluate the research's strengths and weaknesses, make informed judgments, and appropriately use the findings. Ultimately, it can improve the quality of research and enhance the overall understanding of a particular phenomenon.

In this study, delimitations have been identified. Firstly, both primary and secondary data observations were focused solely on the National Football League (NFL) to investigate the pricing determination of secondary market sellers, attendance demand, and fans' willingness to pay. The current study has delimited the NFL from other sport leagues both within and outside the United States, such as Major League Soccer (MLS), Major League Baseball (MLB), National Basketball Association (NBA), National Hockey League (NHL), English Premier League (EPL) in England, and National Ruby League (NRL) in Australia. Each league has distinct policies, structures, fans, and characteristics that could influence major objectives of this study. Additionally, during the COVID-19 pandemic, each league had its own health and protocol policies to manage risks associated with COVID-19. For instance, while MLB canceled the 2020

Spring Training games and delayed the regular season games, NBA continued its games in a bubble (i.e., an isolated venue) in Orlando, Florida, without allowing physical attendance of fans (i.e., fans could only participate virtually).

The second delimitation of this study pertains to the exclusion of international series. In 2022, the NFL announced five games for its international series in London, United Kingdom, Munich, Germany, and Mexico City, Mexico. International series were excluded from this study for several critical reasons. Firstly, despite COVID-19 being a global threat, each location where an international series game is held has different circumstances from the United States, such as varying numbers of COVID-19 cases and deaths, distinct economic impacts, different currency statuses, and different price-control policies. Additionally, the designed face value of tickets could be different due to differences in stadium structures. While regular NFL season games are a typical sporting event that fans and consumers expect to have every year, international series games can be considered as a special event outside of the United States. Therefore, international fans may have fewer opportunities to participate in NFL sporting events, leading to unusually high demand and prices.

After discussing the delimitations, it is also important to acknowledge the limitations of this study. The primary limitation is that the study relied on listed ticket prices rather than transaction prices. While listed prices can indicate how resellers value each game and reflect consumer interests, transaction prices would provide more accurate information about consumers' willingness to pay. In essence, while the secondary market ticket price is acknowledged to be demand-driven (Shapiro & Drayer, 2014), since resellers' pricing decisions do not necessarily mirror the willingness of fans to pay for a ticket, it cannot be considered the perfect representation of the market's demand.

A limitation of this study is the need to include COVID-19's effects on the variables being studied as well. This study only considered COVID-19 cases and deaths and did not encompass other circumstances or influences. The COVID-19 pandemic has had far-reaching effects on society. One of the most significant impacts has been on health and well-being, with millions worldwide affected by this highly infectious respiratory illness, which has resulted in widespread illness, hospitalizations, and deaths, hitting vulnerable populations the hardest. Additionally, COVID-19 has caused widespread economic disruption, with businesses shutting down, job losses, and financial instability. Specifically, economic issues have exposed existing economic inequalities, with marginalized communities suffering the most.

The pandemic has also led to social isolation and reduced social interactions due to restrictions on gatherings and social distancing measures. Social isolation could increase loneliness, mental health problems, and other social challenges (Wang et al., 2017). Educational systems worldwide have been disrupted, with many schools and universities closing or shifting to online learning, creating challenges for students, teachers, and parents and widening existing educational inequalities (Doyle, 2020). Finally, the pandemic has also had significant political impacts, with debates over government responses, concerns over civil liberties and human rights, and impacts on elections and political systems (Redbird et al., 2022). If researchers could comprehend and incorporate the various impacts of COVID-19, it would prove more advantageous for stakeholders in the sport industry.

Lastly, the current study faced a statistical limitation regarding the data observations. Despite satisfying the linearity and homoscedasticity assumptions, the normality assumption was violated in the multilevel model analysis, even after applying log-transformation. However, I proceeded with analyzing the data due to the robustness of multilevel models on data distributions (e.g., Gelman & Hill, 2006; Schielzeth et al., 2020), large sample size, and the Central Limit Theorem (CLT). Specifically, multilevel models are known to be less sensitive to deviations from normality assumptions, making them a suitable method for real-world datasets with non-normal data distributions (Gelman & Hill, 2006). Additionally, the CLT suggests that the sampling distribution of a large enough sample size will be normally distributed, regardless of the underlying population distribution. Lastly, the skewness and kurtosis of the data were within acceptable ranges, further supporting the analysis of the data despite the violation of the normality assumption.

Chapter Summary

To gain insight into customers and fans, sport organizations need to understand secondary market ticket pricing, attendance demand, and consumer willingness to pay. By doing so, they can improve marketing and revenue generation strategies, enabling them to compete and survive in the market. Many researchers in the field of sport marketing and pricing have emphasized the importance of ticket pricing and transaction prices across various sport leagues globally (e.g., Diehl et al., 2016; Drayer et al., 2012a; Kemper & Breuer, 2015, 2016; Lee et al., 2023; Popp et al., 2018; Sanford & Scott, 2016; Shapiro & Drayer, 2012, 2014; Shapiro et al., 2016a, 2021). Despite the widespread impact of COVID-19 on the sport industry, the full extent of its effect on the sporting event ticket market, consumer behavior, and fan demand remains to be determined. This study explored how the pandemic has influenced ticket pricing strategies, the number of attendees, and consumer willingness to pay in the NFL. The second chapter (Chapter II) reviews existing literature on factors affecting ticket pricing, attendance demand, consumer willingness to pay, and the pandemic's impact on related industries: hospitality and tourism sector. Chapter III describes the data collection and analysis methods with research questions and hypotheses. Chapter IV reports the research findings, and Chapter V provides an in-depth discussion of the results and future study direction.

CHAPTER II

LITERATURE REVIEW

Development of Ticket Pricing Strategies

Ticket pricing is crucial from a marketing and profitability standpoint within the sport industry. In both collegiate and professional sport, ticket pricing strategies and consumer demand have been deemed critical to organizations' revenue. According to Dees et al. (2021), although gate revenue is the second highest revenue source following broadcasting rights, it has been the most profitable source until 2017. Other studies (e.g., Fort & Quirk, 2010; Shapiro & Drayer, 2012) identified ticket sales as the most profitable way to maintain and generate revenue. However, ticket sales are more than a primary revenue source for sport organizations; they are a gateway to ancillary revenue opportunities such as parking, concessions, and merchandise. As ticket sales account for the most significant proportion of sport organizations' revenue and marketing, scholars have examined several pricing strategies (Rishe & Mondello, 2004; Shapiro & Drayer, 2012; Shapiro et al., 2021) in relation to market structures and attendance demand.

Fixed Ticket Pricing

Research on ticket sales and prices emerged in the sport industry between the late 1990s and early 2000s. Howard and Crompton (2014) pioneered research on ticket prices in the NFL, detailing the pricing strategies these teams used to determine ticket prices for sporting events. However, their study featured an unusual data collection process (i.e., personal communication; informal conversations with participants) compared to typical methods of collecting data (e.g., survey, formal interview, and secondary data). To advance the theory and practice of Howard and Crompton, Reese and Mittelstaedt (2001) later scrutinized NFL ticket pricing strategies using a more standard procedure: A questionnaire consisting of 10 questions using the Likert scale was used in a survey. Although the study was intended to examine NFL teams' processes for determining ticket prices, several other factors (e.g., star players, team performance, weather conditions, and media coverage) that could affect fan attendance were also covered in questionnaire items. NFL ticket operators were found to consider team performance, organizational revenue needs, and average ticket prices as the most critical factors in ticket pricing. Understanding characteristics that influence fan demand became particularly important with technological advances (e.g., broadcasting) and sport industry revenue. As previously mentioned, empty stadium seats were one of the greatest concerns because fans have diverse options to participate in sporting events (Burton & Cornilles, 1998).

With these fundamental findings on ticket pricing, Rishe and Mondello (2003) sought to compensate for the limitation of Reese and Mittelstaedt's (2001) methodology. Surveying ticket operators (i.e., employees responsible for determining and adjusting organizations' ticket prices) was at once a strength and weakness of Reese and Mittelstaedt's study. Despite revealing key factors that decision-makers consider when implementing pricing strategies, results were not precise enough to measure the relationships between focal factors and ticket price determination (e.g., how each factor might increase or decrease ticket prices across a team's season). Thus, Rishe and Mondello (2003) analyzed data (i.e., examined factors with ticket prices in a given year) to explore attributes that could inform ticket prices across NFL teams based on observations from 1996 to 2001.

Rishe and Mondello (2003) revealed several findings that enriched previous knowledge of ticket pricing. First, average ticket prices indicate that each team sets different prices based on team performance, fans' income level, population, and stadium age (e.g., the first year of a new stadium). Second, a team's previous season record (e.g., winning percentage and playoff status), new stadium, and the degree of seasonal change in average ticket prices significantly affected teams' pricing decisions. Third, although team owners and organizations raised ticket prices each year and attributed these increases to payroll, changes in payroll were not found to influence differences in average ticket prices. However, due to each city's unique circumstances (e.g., market size and presence of other professional or collegiate sport teams), the authors' models could not explain over 50% of the variation in pricing. Observable and unobservable variables hence affect ticket prices.

Rishe and Mondello (2004) subsequently extended their examination of ticket price decisions across the United States' four major professional sport leagues: Major League Baseball (MLB), the NFL, the NBA, and the National Hockey League (NHL). Their study provided essential information about ticket pricing, especially regarding how factors differentially influence these leagues. For example, whereas MLB and NBA teams purportedly increased ticket prices due to larger payrolls, NFL and NHL teams' ticket operators were unaffected by payroll changes. These findings bolstered the comprehension of ticket pricing by examining how the same factors operate differently and similarly in each professional sport league. Sport organizations should not assume they will see the same results as other leagues.

Considering new ticket pricing findings in the NFL, Rishe and Mondello (2003) introduced an important concept based on supply and demand in the ticket market: the relationship between consumer demand and ticket prices. Specifically, when the ticket supply is fixed for each team with a fixed NFL stadium capacity, ticket price changes depend on varying demand levels per season. Theoretically, organizations have a fixed number of tickets to sell;

sport fans' demand (e.g., willingness to attend a game) is a core pricing determinant. Moreover, as mentioned, organizations have striven to understand factors driving consumer demand for several reasons. First, a considerable number of sport organizations struggled to renew and sell season tickets in the past. Second, NFL teams have faced obstacles such as low advertisement rates during broadcasts. Interest in sport decreased, as exemplified by empty seats (e.g., Burton & Cornilles, 1998). Lastly, in the past, professional organizations could rarely easily sell their stadiums' naming rights. In sum, teams have wrestled with increasing (or at least maintaining) revenue amid lower attendance and waning market interest.

Demand-Driven Ticket Pricing and Attendance Demand

As attendance demand became a primary concern in revenue generation and price determination, sport organizations started considering a pricing strategy that reflected fan demand: variable ticket pricing (VTP). Organizations gradually realized that each game holds differential value for consumers. Sport fans are not willing to pay the same ticket price for every game. Although the sport ticket market adopted VTP in the early 21st century, this strategy prevailed in the leisure industry (e.g., airlines and hotels) for several decades prior. VTP's strength in the leisure industry is flexibility. Sport organizations usually anticipate attracting more attendees by offering reasonable prices. Options are usually based on four major price determinants (i.e., part of the season, day of the week, holidays, and opponent quality, including the number of star players) throughout the season for the same seat (Rascher et al., 2007). Prices are determined overall based on potential interest. Starting with teams in the NBA (e.g., Milwaukee Bucks) and the MLB (e.g., Colorado Rockies, San Francisco Giants, and St. Louis Cardinals), the era of consumer demand infused the sport ticket market with VTP characteristics.

Other professional organizations (e.g., the NHL) and collegiate football teams later started to employ VTP based on expected revenue maximization (Rovell, 2002).

Heilmann and Wendling's (1976) work is considered a pioneering VTP study among demand-based research. The authors examined the effects of discounted Milwaukee Bucks tickets in terms of multiple factors (e.g., weather and player status) on NBA attendance demand. Although the Bucks were the only team to leverage VTP in the U.S. sport industry at the time, Heilmann and Wendling's study had limitations: discounted pricing strategies for 15 games did not fully reflect VTP. The Bucks did not fully adopt VTP to determine ticket prices. Even as several professional and collegiate sport organizations started to adopt VTP to generate more revenue from ticket sales, many teams maintained fixed pricing due to doubts about demand-based strategies; sport organizations were highly skeptical of VTP.

Whereas sport teams were suspicious, scholars documented the effectiveness of demand-driven pricing. Growing interest in fan demand and a limited understanding of VTP spurred pricing research. Different from fundamental pricing efforts, consumer demand and attendance studies (e.g., Fort, 2004) focused on pricing strategies reflected by consumer demand. For example, factors that affect fixed ticket pricing (e.g., the day of a game, home and away teams' winning percentages, individual players' performance, and weather) and other variables were shown to influence game attendance (McDonald & Rascher, 2000). Numerous concepts and theories (e.g., price discrimination and social exchange theory; Howard & Crompton, 2004) have also been viewed as critical based on elements that can increase and decrease consumer demand in the ticket market. Lastly, price elasticity, significantly affected by demand elasticity, has been tied to profit maximization (Boyd & Boyd, 1996; Noll, 1974). For instance, in demand-driven ticket pricing, prices increase with higher demand and vice versa.

Ongoing research on sport fans' demand and their physical presence in the stadium has unearthed positive findings about the relationship between demand-driven pricing and organizational revenue. Games offer individual fans unique value. Exactly which strategy brings more money was at first unclear. Rascher et al. (2007) addressed the effectiveness of demand-driven pricing by revisiting VTP in the MLB. Findings sparked greater intrigue in the correlation between ticket prices and fan demand. Researchers kept documenting the positive impact of demand-driven pricing. Censored regression and elasticity analysis of observations from the 1996 MLB season indicated that VTP could generate approximately $590,000 in additional annual revenue for each team. Whether variable pricing causes ticket prices to increase or decrease depends on the game and fans' interest. In general, however, organizations can attract attendees more regularly with flexible prices. Given the importance of VTP for revenue generation, variable pricing has afforded organizations opportunities to engage in public relations with local municipalities (Rascher et al., 2007): sport franchises have leveraged this strategy to cultivate relationships with communities for beneficial public support (e.g., building or renovating a ballpark) and attracting new spectators to the stadium. Demand-based ticket pricing prevailed as VTP was confirmed as a useful revenue management tactic and public relations approach.

While variable pricing strategy began to dominate sport organizations' ticket pricing strategies by providing economic and social benefits, a new demand-driven pricing strategy emerged: dynamic ticket pricing (DTP). DTP's arrival in the sport industry showed how attendance demand influences real-time ticket pricing. VTP is not considered a fully demand-driven approach, even though ticket prices are determined by demand-driven factors. Specifically, primary market sellers (e.g., professional teams) set ticket prices at least two weeks prior to a game day based on predicted consumer demand in relation to various factors. Therefore, sport teams had difficult times reflecting demand-based changes in ticket prices during the season. Moreover, with VTP, sport organizations only focused on four factors (e.g., the day of a game, time of the season, team quality with star players, and holidays) despite additional considerations that could affect consumer demand and ticket pricing.

> With the lack of knowledge on fluctuating consumer demand in the market based on VTP, DTP has been adopted as a novel strategy in the primary market. DTP refers to a flexible price setting process with respect to market dynamics (supply and demand fluctuations), sectoral price discrimination according to the [willingness to pay] of the individual customer (customer group) regarding specific product properties like e.g., quality, intertemporal price discrimination as well as the capacity and inventory conditions of the sellers/producers['] facilities. (Schwind, 2007, p. 29)

Distinct from VTP, DTP strategies introduced a new standard to the sport industry with daily and more precise (e.g., by hour and by minute) price changes based on attendance demand (Drayer et al., 2012b; Paul & Weinbach, 2013; Shapiro & Drayer, 2012, 2014).

VTP appeared in the leisure industry before the sport industry, but DTP was common in the airline and hotel sectors. In the sport industry, the San Francisco Giants implemented dynamic pricing as a new revenue management system. Shapiro and Drayer (2012) examined why DTP is appropriate for sport ticket markets based on criteria from previous studies (e.g., Kimes, 1989; Kimes et al., 1998). Such criteria are diverse: market segmentation (e.g., gender, season ticket status, and education level); perishable inventory (i.e., unsold tickets cannot be used after a game); products sold in advance (i.e., fans have multiple opportunities to purchase tickets prior to a game); low marginal sales costs (when sport organizations sell tickets at lower prices, they expect fans to spend considerable money on food, beverages, parking, and merchandise); high marginal production costs (i.e., similar to the hotel and airline industries, creating additional seats would be unrealistic); fluctuating demand (i.e., as VTP shows, fan demand changes based on multiple factors); and predictable demand (i.e., studies on both fixed and demand-driven ticket pricing have identified factors affecting sport event consumption). Drayer et al. (2012b) observed why DTP can be effective for revenue generation. Nufer and Fischer (2013) then demonstrated why major European soccer leagues should implement DTP based on an investigation of Bayern Munich football club in the Bundesliga (the first soccer division in Germany).

Following theoretical studies of DTP in the sport industry, more empirical research has emerged (e.g., Kemper & Breuer, 2016; Paul & Weinbach, 2013; Shapiro & Drayer, 2012, 2014). Shapiro and Drayer (2012) selected 12 San Francisco Giants games in the 2010 season, as this team was the first professional sport organization to employ DTP in the United States. Results revealed two key trends: 1) tickets' average dynamic pricing increased significantly as the game date neared, and 2) DTP has a potential floor and ceiling. Notably, although time influences DTP, ticket prices neither increase nor decrease at a certain point—professional organizations must consider a price ceiling and floor when raising ticket prices as the game day approaches. Although these strategies may not be ideal for selling more tickets, unsold tickets do not pose a major risk for sport organizations. Profits from ticket sales can consume a larger percentage of revenue while merchandise sales, sponsorships, stadium naming rights, and other sources maintain earnings. Nevertheless, according to Moore (2010), the Giants generated an additional $450,000 from ticket sales when applying DTP to only 5% of seats in Oracle Park (formerly AT&T Park); ticket revenue increased 7% in the following season (Kahn, 2011). DTP strategies and revenue have spurred research uncovering the factors that affect dynamic pricing (e.g., number of all-star players, starting pitchers' earned run average, division status, day of the week, home and away teams' winning percentages, and weather conditions; Paul & Weinbach, 2013; Shapiro & Drayer, 2012, 2014).

As the primary market has witnessed meaningful revenue increases from DTP, multiple MLB teams (e.g., Houston Astros, St. Louis Cardinals, and Chicago White Sox) have implemented dynamic pricing in subsequent seasons—as have teams in the NHL, Major League Soccer, NBA, and NASCAR. Outside of the United States, English Premier League and other European soccer league teams have demonstrated higher ticket sales revenue with DTP (Nufer & Fischer, 2013). Despite the growth of primary ticket sales with DTP, the secondary ticket market's rise has brought customers an entirely different experience. The secondary ticket market is completely demand-based, with distinct revenue sources between primary and secondary sellers. Ticket sales are resellers' only revenue source; in other words, unsold tickets can represent critical losses for secondary ticket market sellers.

The secondary ticket market started with person-to-person sales (e.g., purchasing tickets from acquaintances), scalpers, and brokers (Drayer & Martin, 2010). Many early members tended to engage in unethical business practices. However, with continued growth, the secondary ticket market began to gain legitimacy in the sport industry. An expanding number of customers and platforms spawned partnerships between secondary market organizations and primary market sellers. Sport ticket resales were deregulated as a result. As the ticket resale business has established, secondary marketplaces have swelled into a multi-billion-dollar industry with advanced technologies (e.g., StubHub, SeatGeek, and eBay). The secondary market's total volume jumped by approximately $1.4 billion between 2011 and 2013 (Rishe et al., 2015).

According to Juniper Research (2021), sport fans are projected to spend $9 billion more on secondary ticket platforms by 2023.

The secondary ticket market is expected to continue attracting customers. It is, therefore, important to understand the factors that color attendance demand in this market. Two main types of data have been collected to examine the effects of numerous variables on ticket pricing: secondary data (e.g., Drayer & Shapiro, 2011; Drayer et al., 2012b; Kemper & Breuer, 2016; Soebbing & Watanabe, 2014; Watanabe & Soebbing, 2017) and survey data (Ninomiya, 2015; Reese & Mittelstaedt, 2001; Shapiro et al., 2016b). Most studies have developed linear regression models to explore the relationships between ticket pricing and select variables. Although linear regression is simple to implement, handles overfitting, and is well suited to linearly separable observations, several disadvantages have been identified (e.g., Zapotichna, 2021). Linear regression models can suffer from multicollinearity, high sensitivity to outliers, and noise. Some work (e.g., Dwyer et al., 2013; Reese & Bennett, 2013) has thus used other types of multivariate analysis in ticket pricing research to uncover relationships between factors and correlations between dependent and independent variables. For example, multivariate linear modeling (MLM), multilevel modeling, and multivariate variance analysis can better be employed to understand the relationships between dependent and independent variables. Pricing studies can also uncover distinct effects of the same factor on ticket pricing based on linear regression models and MLM.

Meanwhile, researchers have investigated attendance demand and ticket pricing based on six common categories (e.g., Schreyer & Ansari, 2022; Shapiro & Drayer, 2014): time-related variables, game-related variables, environmental variables, team performance variables, individual performance variables, and ticket-related variables. Regarding time-related variables, studies have generally concerned three: 1) day of a game (i.e., weekday or weekend; Bovd & Krehbiel, 2003; Falls & Natke, 2016; McDonald & Rascher, 2000; Rascher et al., 2007; Shapiro & Drayer, 2014; Shapiro et al., 2021); 2) impact of the number of days remaining before a game (Harrington & Treber, 2014; Shapiro & Drayer, 2012; Sweeting, 2012; Sweeting & Sweeney, 2015); and 3) part of the season (e.g., early, middle, or late; Lemke et al., 2010; Shapiro & Drayer, 2014; Shapiro et al., 2021). Specifically, in relation to the day of a game, before participating in an entertainment event or embarking on a vacation, deciding exactly when to do so is a significant consideration.

Moreover, the day an event occurs (i.e., on a weekday or weekend) is important when merchants adjust ticket prices and measure the number of attendances based on the relationship between day and demand. Research in the leisure and hospitality industries has confirmed the impact of the day of the week on ticket pricing and demand (Forrest & Simmons, 2006; Malasevska & Haugom, 2018; Schamel, 2012). Sport research has also shown that the day of the week is significantly correlated with prices and attendance demand based on fans' willingness to attend weekday and weekend MLB games. Most findings have indicated that sport fans prefer to attend weekend games because of the high opportunity costs associated with viewing weekday games due to work (McDonald & Rascher, 2000). Tickets to weekend games thus tend to be priced higher than tickets for weekday games (e.g., Rascher & Solmes, 2007).

Considering the impact of the day of a game on ticket pricing and attendance demand, scholars have found that time affects ticket price movement, especially as the event date nears (Harrington & Treber, 2014; Shapiro & Drayer, 2012; Sweeting, 2012; Sweeting & Sweeney, 2015). Based on secondary market data (i.e., eBay and StubHub), Sweeting (2012) noted that prices dropped 40% as the date of an MLB game approached. Additionally, Shapiro and Drayer

(2012) discovered that ticket prices in the secondary market fluctuated (i.e., increased and decreased) long before a game day but declined as the game day neared. The relationship between time and ticket price applies to MLB and NFL games: Harrington and Treber (2014) pointed out that Superbowl ticket prices fell a few days before the game. The research suggests that sellers reduce ticket prices when approaching game day to minimize the risk of their tickets remaining unsold. Sport event tickets are perishable goods that are worthless after a certain time (i.e., tickets generally cannot be sold once a game has started), and sellers lower prices to generate profits.

Lastly, prior studies have considered the overall sport season in addition to the game day and time sensitivity. In the sport industry, as months are expected to have a significant relationship with ticket prices and the number of attendeess, studies have examined part of the season considering important determinations of price and demand (Forrest & Simmons, 2006; Lemke et al., 2010). For example, according to Shapiro and Drayer (2014), the regular MLB season consists of the early season (April and May), mid-season (June and July), and late season (August to October). The part of the season is integral to teams' post-season (i.e., playoff) status. As the end of the season approaches, teams compete for limited post-season slots or a wildcard spot. Late-season games thus hold more weight than those early in the season.

Team performance variables represent another core factor. Scholars have considered the home team's winning percentage, the away team's winning percentage, and a team's playoff status in the previous season (Drayer & Shapiro, 2009; Drayer et al., 2012b; Forrest & Simmons, 2002; Humphrey et al., 2009; O'Hallarn et al., 2018; Rishe & Mondello, 2003, 2004; Schofield, 1983; Shapiro & Drayer, 2014; Shapiro et al., 2021; Watanabe & Soebbing, 2017). Researchers have especially emphasized team performance in relation to game quality (e.g., Drayer &

Shapiro, 2009). Statistically, team performance consists of offensive and defensive statistics and winning percentages. Offensive and defensive statistics can be further divided into myriad factors depending on sport type. Individual performances contribute to overall team performance on the field. Team performance significantly affects ticket pricing and attendance demand (e.g., Forrest & Simmons, 2002; Lemke et al., 2010).

As a follow-up to earlier literature, upon examining average ticket prices and transactions for 256 NFL regular season games during the 2007–08 season, Drayer et al. (2012a) identified the home team's current winning percentage and the away team's prior season winning percentage as integral predictors of ticket prices for NFL games in the secondary market. Teams' winning percentages can positively influence ticket prices in this market. However, the home team's winning percentage is more influential than the away team's, as shown by transaction prices. Shapiro and Drayer (2014) conversely discovered that the MLB home team's increased winning percentage over its previous 10 games adversely affected secondary market ticket prices. A 25% jump in the home team's winning percentage led to a decline of roughly $16-–– $17 for secondary market transactions. Such discrepancies may have arisen because the authors examined (a) different sport leagues, which may attract different fans; and (b) different platforms, which may possess unique consumer characteristics. Moreover, Gitter and Rhoads (2010) found a positive relationship between winning percentage and attendance demand in minor league baseball. One of the interesting findings of Gitter and Rhoads is that when a local or regional affiliated MLB team has a high winning percentage (i.e., high quality of performance), minor league baseball attendance demand increases.

In addition to the relationship between the current winning percentage and ticket pricing based on attendance demand, a team’s previous season success (i.e., post-season status) is another important measure of team performance (Drayer & Shapiro, 2009). Boyd and Boyd (1998) argued that, despite having different rosters each season due to trades, free-agent contracts, and drafted rookies, previous post-season status could be determined with a team's winning record to indicate the team's anticipated performance in the upcoming season. At the start of the season, team performance cannot be determined by current winning percentage due to the limited number of games. The role of a team's previous season record has been noticed in individual sport as well. For example, in wrestling, the previous season record is used to predict current-season success and failure based on performance expectations (Burton & Martens, 1986).

Even though individual performance is part of team performance, the impact of star players has been analyzed as an individual performance metric (Jane, 2016; Lewis & Yoon, 2018; Rivers & Deschriver, 2002; Shapiro & Drayer, 2014). Research in various sports has examined this element, which can boost a team's quality based on personal performance. Star players' performance and appearance are significantly positively correlated with attendance demand (Lewis & Yoon, 2018; Rivers & Deschriver, 2002). Jane (2016) revealed that the number of event attendees increases with the presence of star players at home and away from NBA games. Star players can therefore affect ticket prices in the secondary market, which is demand-driven. Additionally, Shapiro and Drayer (2014) observed the positive impact of the number of all-star players on the away team relative to ticket prices: the appearance of star players increased ticket prices on the market.

Researchers have further ascertained that game-related variables influence ticket pricing and attendance demand (Butler, 2002; Lemke et al., 2010; McDonald & Rascher, 2000; Shapiro & Drayer, 2014). Game-related variables such as divisional and inter-conference games have been studied in sport research. For several reasons, division and conference affiliations are particularly significant in most sport leagues. Firstly, teams play more than half of their regular season games against other teams in the same division or conference. Secondly, teams in the same division or conference compete for playoff spots. Finally, rivalries often exist among teams within the same division or conference, which can lead to an increase in fan attendance, as per the study conducted by Lemke et al. (2010). Although numerous studies have indicated that division and conference games are significantly correlated with attendance demand and ticket prices (Butler, 2002; Lemke et al., 2010; McDonald & Rascher, 2000; Shapiro & Drayer, 2014), other scholars have not identified any significant relationship (Drayer et al., 2012a). Still, some studies (e.g., Tainsky, 2010) have raised questions about consumers' preferences for divisional games due to scheduling in U.S. sport leagues. As Tainsky (2010) stated, consumer demand and ticket prices could be higher for non-divisional games because fans have fewer chances to attend games against specific teams from other divisions.

Environmental factors are critical determinants of ticket prices and attendance demand, including the pandemic (i.e., COVID-19). Weather is a major aspect (Butler, 2002; Drayer et al., 2012a; Howell et al., 2015; Kemper & Breuer, 2016; Lemke et al., 2010; Shapiro & Drayer, 2014). In particular, weather and sport events are significantly associated with the venue. Apart from a handful of select leagues (e.g., the NBA and NHL), most teams' stadiums do not have the roofing to protect spectators from inclement weather. Similar to research on game attendance amid the pandemic, weather-related findings have been contradictory. Popp et al. (2019) discovered that even though rain significantly affected attendance demand, the temperature did not; however, Schreyer et al. (2019) came to the opposite conclusion. More research is needed to determine specific price and demand changes in forecasted weather conditions due to controversial findings and a lack of specifications on determining weather conditions during game time.

Fundamental variables that inform ticket pricing have also been discerned, including the number of available tickets (e.g., Dwyer et al., 2013; Shapiro et al., 2016b; Wann et al., 2004). Pandemic restrictions have especially constrained secondary market sellers' and buyers' ticket availability until July 2021. Most professional sport organizations and college sport leagues have conducted games without spectators or with limited seating capacity, although they began to ease their restrictions from around the middle of 2021. These unprecedented circumstances highlight the notion of scarcity in ticket pricing. Scarcity has been defined in terms of high-value stones from mines: "The demand for the precious stones arises altogether from their beauty. They are of no use but as ornaments; and the merit of their beauty is greatly enhanced by their scarcity, or by the difficulty and expense of getting them from the mine" (Smith & Wight, 2010, p. 112). Meanwhile, as scarcity and limited availability provide customers with more positive impressions of products, business organizations have leveraged the notion of scarcity as a marketing strategy.

Tickets for sport events have been explored based on scarcity, as Wann et al. (2004) discussed. First, if commodity scarcity works properly, consumer goods should be useful, exchangeable, and possessive based on the commodity theory per Brock (1968) and Brock and Brannon (1992). Second, as in the stone example above, sport tickets can be advertised based on their limited nature (Cialdini, 1994). Just as limited supply is emphasized to increase a product's value, ticket prices can be tied to a limited number of seats or fixed stadium capacity to encourage customers to consider a ticket a high-value product. Scholars have identified scarcity as a highly efficient marketing tool; however, its impact cannot be guaranteed under unique circumstances such as COVID-19. As scholars have yet to fully address the impacts of the pandemic on ticket prices and markets, research on ticket pricing and consumer demand during this time can shed new light on effective sport ticketing practices.

The factors that shape attendance demand and ticket pricing in the secondary market can help primary and secondary market sellers determine which games customers may like to attend. Understanding sport fans' preferences can also aid sellers in adjusting ticket prices per game. Sport organizations and resellers have a greater chance of generating more revenue by knowing what customers wish to consume. Professional and collegiate sport teams should hence enact more precise marketing strategies tailored to what customers would like to see, hear, and experience.

Consumers' Willingness to Pay

As discussed in the ticket pricing and attendance demand literature, pricing is one of the most essential revenue generating and marketing tools. Consumers' willingness to pay (WTP) has emerged to be understood as the most effective pricing strategy. As the example in Chapter I indicates, economic attributes constitute one of several variables that distinguish consumers' WTP given equivalent demand. Before discussing additional factors in WTP, it is necessary to understand why a gap exists between sellers' listed prices and consumers' WTP for the same product. The market structure is partly responsible; besides a few markets with unique circumstances (e.g., auctions), product prices are generally fixed.

Distinct behaviors and purposes further generate disparities between sellers' asking prices and consumers' WTP: sellers and buyers assign varying values to factors that affect product prices (Carmon & Ariely, 2000). For instance, sellers focus more on the expenses (e.g., costs of materials and human labor) required to produce merchandise when deciding on a price. Buyers tend to be more concerned about discounts and the prices of similar products. Lastly, whereas most sellers try to maximize their profits through higher product prices, buyers are more likely to spend conservatively (i.e., by purchasing products with lower prices). Given sellers' and buyers' characteristics and objectives, examining factors informing product prices and variables shaping consumers' WTP is critical. By comprehending WTP, organizations can have more opportunities to sell products and minimize unsold goods. In other words, they will have greater chances to increase their sales revenue through a high sales volume using either fixed or customized prices. Organizations can also implement ideal pricing strategies based on the combined effect of price determinants and WTP.

Several decades ago, well before businesses adopted WTP as a revenue management and marketing strategy, the concept was discussed in economic research alongside other theories and terms (e.g., volitional psychology and price point of willingness to sell; Davenport, 1902)—the early development of WTP in numerous domains. For example, researchers began to uncover factors affecting WTP, such as how the perceived value of human life changes with risk (e.g., Jennings & Jennings, 2000), individuals' WTP for art and performance (Thompson et al., 2002), the general public's WTP for public programs to prevent domestic violence (Sorenson, 2003), and individuals' WTP to boost the quality of cultural institutions in metropolitan areas (Clark & Kahn, 1988). Results have revealed significant differences and relationships between WTP and consumer demand. Whereas WTP denotes the maximum price consumers will pay for a single unit of a product, service, or public good, consumer demand represents buyers' responses to sellers' prices based on buyers' WTP. Put another way, consumer demand indicates how many people are interested in a specific good; WTP shows whether customers are willing to buy it in monetary terms.

WTP came to the core of business marketing as researchers began to discover its contributions to price setting and revenue management despite being conceptually distinct from consumer demand. Specifically, initial marketing studies of WTP (e.g., Goldberg et al., 1984; Kohli & Mahajan, 1991) developed calculation methods to estimate the degree. Goldberg et al. (1984) and Kohli and Mahajan (1991) focused on different price levels in conjoint analysis—one of the most popular marketing strategies—while considering correlations with other product attributes and profit maximization. Cameron and James (1987) adopted an alternative technique, contingent valuation, to measure WTP in terms of cost–benefit analysis, environmental elements, and marketing mix components. The growing interest in WTP has inspired studies on the accuracy of measurement strategies and the proposal of new models to assess consumers' WTP for goods (Krishna et al., 2006; Schmidt & Bijmolt, 2020; Wang et al., 2007; Wertenbroch & Skiera, 2002). WTP studies have expanded across multiple industries, covering topics such as the following: identical items and points of purchase with incentive-compatible WTP (Wertenbroch & Skiera, 2002); customized pricing circumstances, including online auctions (Chan et al., 2007; Drayer & Shapiro, 2009); and WTP in the health industry (McDougall et al., 2020).

Given the preceding overview of similarities and differences between WTP and consumer demand, several price-related concepts pertain to WTP. Pricing strategies constitute a major factor affecting consumers' WTP. First, Monroe (2002) introduced the concept of a reference price (RP). "What is reference price? Definition of reference price, reference price meaning (2019)" defined RP as "the cost at which a manufacturer or a store owner sells a particular product, giving a hefty discount compared to its previously advertised price" (Linking section, para. 1). RP has also been deemed competitive pricing based on its function; the price of a sold product does not vary drastically from competitors' prices. Essentially, sellers set prices just below those of competitors to sell more than other retailers. Different prices for the same products lead consumers to purchase if they consider the price reasonable. RP is significantly related to purchase behavior and WTP (Monroe & Petroshius, 1981). It is therefore important to understand this concept and how it affects consumers' WTP.

Following general knowledge of RP, two specific types apply to WTP: consumers' internal RP (IRP) and external RP (ERP). IRP has also been called the "memorized price" (Le Gall-Ely, 2009) and is formed based on the prices that consumers recall from prior purchases (Rajendran & Tellis, 1994). For example, if season tickets for a specific team were previously $1,000, then season ticket holders will consider that price when purchasing tickets for the next season. In other words, IRP is not determined by the seller; it is the price consumers expect to pay based on their experiences with the same/similar product. Studies (e.g., Mazumdar et al., 2005; Nieto-García et al., 2017) have shown that IRP greatly affects consumers' purchase decision-making process. IRP informs WTP, as the most recently experienced price is highly influential (Nasiry & Popescu, 2011): when IRP is high, so is WTP and vice versa. In sum, although IRP is mostly shaped by the most recent purchase price, it can involve other aspects as well.

Another key RP is ERP. Different from how IRP is shaped in the market, ERP is determined by sellers taking into consideration external information (Biswas & Blair, 1991; Grewal et al., 1998; Gross et al., 2021; Kopalle & Lindsey-Mullikin, 2003; Lichtenstein & Bearden, 1989). Retailers have used ERP as a marketing strategy. Prices are highlighted in advertisements based on external information (e.g., promotions, competitors' prices, and points of purchase). Therefore, whereas IRP is an invisible price held in consumers' memory, ERP is a visible price that customers can see in stores. When retailers offer a promotion for a product, they display two prices—the original price and promoted price—to provide deduced price information. Grewal et al. (1998) identified the most famous form of ERP as "Compare at $X." While IRP affects consumers' WTP, scholars (e.g., Lichtenstein et al., 1991) have uncovered a significant inverted U-shaped relationship between consumers' price expectations and difference between ERP and initial price expectations. Specifically, "as the difference between ERP and subjects' initial price expectations increases, subjects' updated price expectations increase to a point and then start to decrease" (Kopalle & Lindsey-Mullikin, p. 225). Price expectations heavily affect consumers' purchase decisions (Kalwani & Yim, 1992; Kalwani et al., 1990). Notable impacts on consumers' WTP underline the need to consider how buyers develop IRP and ERP and how these prices guide purchase decisions.

Another relevant price category is acceptable price. WTP is strongly affected by the acceptable price range/margin. As Le Gall-Ely (2009) pointed out, WTP represents the ceiling of a consumer's acceptable price margin. The RP is a specific price tied to consumers' experiences and retailers' competitive pricing strategies; the acceptable price is suggested by a product's price range (Rao & Sieben, 1992). Regarding sport and leisure activities, Avery et al. (1990) suggested that an acceptable price can be defined based on potential risk (e.g., death and injury). The concept of an acceptable price applies in multiple domains. This dissertation focused on consumer goods. Acceptable price is discussed in the following paragraphs to clarify how minimum and maximum acceptable prices (e.g., WTP) are created in the market.

Starting with social judgement theory (e.g., Sherif, 1963), an acceptable price range reflects the most and least amount of money buyers are willing to pay based on a product's expected value (Dodds & Monroe, 1985; Gabor & Granger, 1966; Jeong & Jang, 2019; Nasser et al., 2019). This range captures a product's perceived quality. When the price exceeds the highest point of an acceptable range, the product is seen as overpriced and falls into an upper-level category that shoppers cannot consume (Rao & Sieben, 1992). Price range is also related to expected product quality. Consumers will be highly skeptical of a product's quality, or will classify the product into a lower-priced category, when it is priced below the lowest point of the acceptable price range. Recognizing consumers' acceptable price range can help organizations mitigate risk in setting prices that either exceed the ceiling or fall below the floor of an acceptable range.

The acceptable price range can move with changes in product prices based on time and the prices of similar products from other stores and brands. Consumers do not encounter identical product prices (Rao & Sieben, 1992). Rather, the acceptable price range is colored by consumers' experiences with and knowledge about a product's price. Additionally, given consumers' distinct behavior and expectations, research (e.g., Lichtenstein et al., 1988) suggests that a width dimension and a level dimension (with either the same or different price points) greatly mold the acceptable price range. For example, two customers can have the same price range width ($10) for a single baseball game. However, the lowest and highest points of the range can vary by level: if both fans have the same level dimension (i.e., the same product category level), they will have highly similar acceptable price ranges (e.g., $10–$20 or $20–$30) with approximately the same price point ($20); if they focus on different category levels (i.e., different center price points: $20 and $100), they will have disparate price ranges (e.g., $15–$25 and $95–$105) for the same baseball game.

Width and level dimensions can vary based on consumers' brand knowledge (Kosenko, 2015). One's acceptable price range is affected by a product's brand name familiarity and position in the market. Minimum and maximum price points are both higher for consumer goods from branded companies versus unbranded companies. Brand knowledge hence determines the level dimension. Studies (e.g., Martín-Consuegra et al., 2007) further imply that customer loyalty and satisfaction significantly affect the level dimension of one's acceptable price range; strong loyalty and satisfaction both increase the lowest and highest price range limits. Moreover, as Chiu et al. (2019) found, consumers' knowledge of price changes is related to price sensitivity and affects the width of acceptable prices: "the weight attached to price in a consumer valuation of a product's overall attractiveness or utility" (Erdem et al., 2002, p. 2). Specifically, high price sensitivity creates a narrower acceptable price range. Changes in product prices can significantly affect the attitudes of consumers with a narrow price range. Alternatively, when consumers display low price sensitivity, price changes should not affect product perceptions (Kung et al., 2002; Rondan-Cataluña et al., 2019; Sirvanci, 2011). The acceptable price range is rooted in expected product prices as informed by multiple variables. Determining an appropriate price range (e.g., the lowest acceptable point and WTP) is key to companies' success (Di Benedetto, 1999; Rondan-Cataluña et al., 2019).

Certain factors influence specific price concepts (e.g., experience, memory, competitors, and knowledge). Understanding the attributes influencing consumers' WTP is crucial when exploring determinants of the highest price consumers are willing to pay. A product's maximum price is directly associated with retailers' revenue and marketing. The ensuing sections address WTP based on factors related to consumer goods. WTP is analyzed thereafter based on ticket pricing in the sport industry.

Customer satisfaction is one of the most impactful factors on WTP, with scholars consistently supporting a significant relationship between the two (Gilal et al., 2018; Homburg et al., 2005; Huber et al., 2001). Before examining how satisfaction affects consumers' WTP, it is necessary to define customer satisfaction. Giese and Cote (2000) noted that, as early studies (e.g., Cardozo, 1965; Oliver, 2014) provided multiple explanations for customer satisfaction, the term cannot be described with a single definition. Giese and Cote (2000) instead provided the three most common conceptualizations: "1) consumer satisfaction is a response (emotional or cognitive); 2) the response pertains to a particular focus (expectations, product, consumption experience, etc.); and 3) the response occurs at a particular time (after consumption, after choice, based on accumulated experience, etc)" (p. 2). In essence, satisfaction is derived from cognitive and affective variables that manifest during product consumption (Oliver, 2014). Earlier work (e.g., Johnson et al., 1995; Olsen & Johnson, 2003) outlined two types of satisfaction: transaction-specific satisfaction and cumulative satisfaction. Transaction-specific satisfaction arises from the customer experience (e.g., service encounters and product transactions) that is directly tied to the transaction process; cumulative satisfaction is based on consumers' overall experiences with a product and associated service from the time of consumption to date. Consumers' satisfaction and WTP share several influencing characteristics (e.g., knowledge, experience, and product value). It is thus integral to consider the relationship between satisfaction and WTP.

Theoretically, consumers' satisfaction and WTP overlap because they each involve similar attributes. Fundamental studies of equity theory (e.g., Adams, 1965; Oliver & Swan, 1989) can partially explain why satisfaction and WTP are related based on fairness in social exchange. Under this theory, equity occurs when a "person perceives that the ratio of his outcomes to his inputs is equal to other's outcome/input ratio" (Pritchard, 1969, p. 177). Within the commercial market, "input" is the amount of money consumers will pay; "output" is the product or service that a retailer provides. Sellers can expect high input when output is high. By contrast, if customers experience lower output compared with input, their WTP will decline due to unequal treatment in the market. A positive relationship between satisfaction and WTP has emerged in numerous industries, such as government public relations with tax, rural business, risk management, and leisure and sport (Casidy & Wymer, 2016; Glaser & Hildreth, 1999; Lee et al., 2013; Simonsen & Robbins, 2003; Thormann & Wicker, 2021). At present, the association between satisfaction and WTP warrants continued attention due to swiftly changing circumstances in the market and among participants.

Approaches to measuring customer satisfaction have been devised in the past decade, with multicriteria satisfaction analysis (MUSA) having been deemed one of the most useful methods. Grigoroudis et al. (2000) and Siskos et al. (1998) developed MUSA in the late 1990s. Grigoroudis and Siskos (2002) described the main purposes of MUSA as follows:

> 1. To evaluate customers' satisfaction level, both globally and partially for each characteristic of the provided service.
>
> 2. To supply a complete set of results that thoroughly reflect customers' preferences and expectations in addition to explaining their satisfaction level.
>
> 3. To develop a decision tool with emphasis on the understanding and applicability of provided results (p. 149).

One strength of MUSA is its ability to fully consider the judgements and preferences of not only customers but also any individual who would like to evaluate satisfaction. Structural equation modeling (SEM) has been widely used alongside MUSA to investigate customer satisfaction (e.g., Saleem & Raja, 2014; Subramanian et al., 2014). SEM is an ideal option for exploring customer satisfaction given its means of identifying measurement error, model fit (test fit), the impacts of observed variables on unobserved variables (latent variables), and model comparability (Mitchell, 1992). Most SEM-based studies on the topic have considered perceived quality and service quality when assessing customer satisfaction (e.g., Yu et al., 2014). Team performance has been used to measure customer satisfaction in the sport industry (e.g., Gray & Wert-Gray, 2012).

Researchers have highlighted the relationship between consumers' loyalty and WTP along with the importance of satisfaction. Loyalty has been defined psychologically and behaviorally in the market as "a deeply held commitment to re-buy or re-patronize a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior" (Oliver, 1999, p. 34). Brand loyalty is grounded in consumers' attachment to a specific brand and repetitive purchase behavior from that brand (Casidy & Wymer, 2015).

Two elements shape loyalty. The first, as mentioned previously, is consumer satisfaction. The level of fairness based on input and output plays a large part in loyalty. The second is consumers' perceived value. The literature has framed perceived value as a core marketing and pricing strategy (Kortge & Okonkwo, 1993; Zeithaml, 1988). This concept refers to the differences between perceived benefits (i.e., what customers gain from a transaction, such as product and service quality) and perceived sacrifices (i.e., the monetary value that customers pay for gains) that customers experience during a transaction. As consumers' acceptable price ranges are subjective, consumers perceive differential value for the same product and service (Kortge & Okonkwo, 1993; Perkins, 1993). Perceived value is also based on the quality of perceived benefits or sacrifices versus competitors and can vary with different service quality for the same product (Eggert & Ulaga, 2002). Loyalty and satisfaction are significantly related. Consumer loyalty has therefore been taken as a mediator to examine the association between consumer satisfaction and WTP (e.g., Casidy & Wymer, 2016). Additionally, loyalty is a pricing strategy. Most work on WTP and loyalty has unveiled a positive relationship between them (Demir et al., 2015; López-Mosquera & Sánchez, 2013; Santos & Schlesinger, 2021).

Prior to delineating the relationship between customer satisfaction, loyalty, and WTP, it is important to consider how related measurement approaches have evolved. Four phases merit attention in customer loyalty assessment (McMullan & Gilmore, 2003): the cognitive phase, affective phase, conative phase, and action phase. The cognitive phase involves customers' perceptions of product/service costs, benefits, and quality as sustainers (McMullan & Gilmore, 2003). Dick and Basu (1994) indicated that four antecedents—accessibility (attitude), confidence (attitude and evaluation), centrality (individual's value system), and clarity (attitude)—should be considered important indicators of customer loyalty. In the affective phase, loyalty entails an individual's emotions (i.e., satisfaction, involvement, preferences, and cognitive consistency). This phase is closely related to one's post-purchase experiences and responses. The conative phase is tied to customers' commitment and willingness to purchase (Dick & Basu, 1994); price changes, sunk costs, and expectations are the three major components that influence customer loyalty in this phase. Lastly, the action phase jointly pertains to individuals' behavior and attitudes. In this phase, inertia (i.e., a customer's commitment to a product/service) and sunk costs largely influence loyalty (Oliver, 2014). These four phases constitute the foundation of customer loyalty measurement. As with customer satisfaction, SEM has been widely employed to evaluate customer loyalty.

WTP has been further explored using consumer demographics (e.g., income, age, gender, and education; Hustvedt & Bernard, 2008; Hwang et al., 2008; Lyford et al., 2010; Shahsavar et al., 2020). Although demographic questions often appear in surveys, these items should not be treated as traditional questions. Participants' demographics can enable researchers to identify similarities and differences between groups. For example, consumers' WTP can vary by income level. Many WTP studies have used the contingent valuation method (CVM) for assessment. Brookshire and Crocker (1981) explained that "Contingent valuation studies are distinguished from traditional benefits assessment practices by their use of survey questionnaires to acquire the data for analysis" (p. 236). CVM has also been used to measure nonmarket values based on survey questions to evaluate individual WTP for products and services.

The method offers noteworthy advantages regarding flexibility and the estimation of total economic value. However, critical limitations apply: CVM cannot accurately depict WTP in terms of environmental quality; the method cannot recall or measure monetary units (e.g., dollars and cents) for environmental goods; and differences exist between hypothetical and actual WTP (Shultz et al., 1998; Venkatachalam, 2004). Meanwhile, several studies have applied SEM for survey methodology (e.g., Marquez et al., 2020; Sánchez-Cañizares et al., 2021). As previously mentioned, SEM allows for analysis of the relationships between observed and latent variables and has been widely used, thanks to several strengths: the ability to estimate and then account for measurement error, estimate the values of unobserved data, measure global fit, and perform tests of direct and indirect effects (Tomarken & Waller, 2005).

Related theories have also linked WTP to profit maximization. First, supply and demand theory explains the interaction between the volume of market resources with respect to WTP. This theory indicates how product prices influence one's willingness to buy or pay. The concept of supply and demand is underpinned by four principles: 1) when supply increases and demand remains constant, prices are expected to decline; 2) when supply decreases and demand remains constant, prices are expected to rise; 3) when sellers maintain the same amount of product and demand increases, prices are expected to rise; and 4) when sellers maintain the same amount of product and demand decreases, prices are expected to decline. In other words, price is determined by changes in supply and demand.

Supply and demand theory captures the general relationship between supply, demand, and price. A unique aspect to understand in relation to WTP is scarcity. Based on Smith and Wight's (2010) definition, scarcity can partly determine the value of products and services. For instance, a commodity's value will exceed its normal range under conditions of high scarcity (Brock, 1968; Cialdini, 1994). Lynn (1991) indicated that scarcity is a fundamental merchandise element that applies to any product based on market conditions (e.g., environmental impact and consumer needs).

Given the possible effects of scarcity in business, this concept represents one of the most popular marketing and profit maximization tools. Suppliers have aimed to shape consumers' purchase behavior by presenting more positive impressions of products to potential customers (Hamilton & Price, 2019; Ku et al., 2012; Stock & Balachander, 2005). Buyers may be especially drawn to advertisements of scarce products; such campaigns can generate positive feelings about a product's uniqueness (Fromkin et al., 1971). In essence, customers' desire to purchase (i.e., WTP) can increase when the number of products available is limited (Lutz, 1989). Organizations across multiple industries have thus leveraged scarcity (e.g., "limited edition") as a marketing and profit maximization tool. Jang et al. (2015) observed limited-edition production series in the luxury brand market. For example, in the sport goods industry, customers have experienced a lack of availability for several products (e.g., product collaborations between Adidas and Prada or joint products between Nike and Off-White). These limited partnerships have attracted many customers in both the primary and resale markets. Some researchers (e.g., Song et al., 2015) have used SEM and measures adapted from Brock (1968) to measure scarcity. Evaluating scarcity messaging can reflect customers' perceived scarcity. However, less is known about how these perceptions inform actual product pricing.

With the potential impact of scarcity on customers' WTP and revenue maximization, price elasticity also affects WTP. The term "elasticity" has been applied in various disciplines (e.g., science) and industries (e.g., airlines, hotels, and sport). In economics, elasticity "measures [the] responsiveness of one variable to changes in another variable" (Greenlaw et al., 2018, p. 108). Within the business domain (e.g., economics, finance, and marketing), elasticity reflects customers' sensitivity to changes in an organization's product-related factors (e.g., product quality, supplied product amount, and product price). Elasticity also affects customers' WTP and organizations' profit maximization (Green & Blair, 1995; Green, 1992). Price elasticity is further related to supply and demand in the market, having been described as the "ratio between the percentage change in the quantity demanded (Qd) or supplied (Qs) and the corresponding percent change in price" (Greenlaw et al., 2018, p. 108). Price elasticity conveys shifts in demand and supply based on changes in price. It is therefore logical that the price elasticity of demand and supply can potentially affect ticket prices in sport.

The price elasticity of demand extends the concept of price elasticity based on consumers' responses in the market. In competitive sectors such as the airline industry, when ticket prices increase for specific airlines, travelers often seek alternate options (i.e., booking through airlines whose prices did not increase for similar-quality seats and the same destination). In this case, airlines can determine percentage differences in demand before and after ticket price changes. Similar to the price elasticity of demand, the price elasticity of supply mirrors changes in supply based on changes in price. Essentially, whereas the price elasticity of demand is used to measure consumer demand in the market based on price changes, the price elasticity of supply is used to measure suppliers' behavior. Customer demand can determine price changes under the price elasticity of supply: high demand inspires higher product prices (Oikarinen et al., 2015). For instance, in the housing market, increasing home prices coupled with high demand will lead suppliers to build more houses. The degree of elasticity can be calculated based on the percentage change in quantity and the percentage change in price (Greenlaw et al., 2018):

Price elasticity of demand = % change in quantity demanded / % change in price

Price elasticity of supply = % change in supplied quantity / % change in price

Greenlaw et al. (2018) identified three levels of elasticity determination. Demand/supply is elastic when the elasticity level exceeds 1; if the level is less than that, then demand/supply is inelastic. Put simply, when the percentage change in the quantity demanded/supplied is higher than the percentage change in price, elasticity results. When the percentage change in the quantity demanded/supplied is lower than the percentage change in price, inelasticity results. Lastly, if the elasticity is equal to 1, then it is unitary and suggests proportional demand/supply responsiveness. Elasticity applies to a product/service that has competitive substitutes; inelasticity arises for a product/service without alternative options. Gas and medicine are inelastic products: substitutes are rare, and such goods are necessities rather than hedonic. Inelastic supply also occurs in the sport industry. Stadium capacity is fixed. As such, sport organizations cannot immediately provide more seats to fans once tickets sell out. Demand elasticity can emerge in the ticket market when consumer interest is low. That is, if a stadium is full to half capacity, then demand can vary based on changes in the prices of unsold tickets.

WTP has been examined for multiple topics in the sport industry, such as mega events (e.g., Atkinson et al., 2008; Walton et al., 2008), non-profit sport (e.g., Johnson et al., 2007), collegiate basketball games (Carmon & Ariely, 2000), NBA games (e.g., Drayer & Shapiro, 2011), and public goods (e.g., stadium financing; Johnson & Whitehead, 2000). WTP has been discussed specifically in the sport ticket market, such as in DTP (Kemper & Breuer, 2016; Shapiro & Drayer, 2012) and the secondary ticket market (e.g., Drayer et al., 2012a; Shapiro et al., 2016b). Consumer demand largely determines sellers' ticket prices. Scholars have typically referred to transactional and listed prices when examining consumers' WTP. However, listed prices have a stark limitation: whereas transactional prices are reflected in consumers' WTP as payment and sellers determine listed prices based on consumer demand. Listed prices thus cannot solely be measured by consumers' WTP. Among studies with common observations, several researchers (e.g., Drayer & Shapiro, 2009; Kemper & Breuer, 2015) collected ticket prices from auction markets that offer buyers customized prices. Consumers' WTP can be measured on auction platforms because buyers place bids based on the seller's starting ticket price. Studies on WTP in this context have shown that the total number of bids, home and away teams' winning percentage, income, ticket face value, and time affect fans' WTP.

WTP has been identified in the sport industry in relation to ticket pricing. However, limited research has integrated secondary and survey data to investigate WTP. Moreover, as the fan experience has changed dramatically with COVID-19 restrictions, scholars should consider how COVID-19 circumstances affect consumers' WTP based on employment, income, limited stadium capacity (seats), and COVID-19 infection risk. Supply and demand theory and the price elasticity of demand and supply may also be strongly related to WTP and the pandemic period.

Impact of Coronavirus Disease 2019

As indicated, besides 9/11 in the United States and related terrorism at mega events (e.g., the Olympics and the World Cup), COVID-19 is the first crisis to ravage the sport industry truly.

Researchers are investigating the impacts of COVID-19 in diverse fields. Sport organizations have sought to manage revenue sources by clarifying the role of COVID-19 in consumer demand. Continuous investigation is needed to prepare risk management strategies as the pandemic is ongoing. Furthermore, even though we cannot predict whether we will face a pandemic similar to or worse than the current one in the future, these discoveries can assist in formulating risk management plans for future pandemics even after the threat of COVID-19 has subsided. Therefore, despite the lack of studies on ticket pricing, scholars have partly uncovered the role of COVID-19 in consumer demand.

First, Reade and Singleton (2021) considered in-stadium attendees in five major European soccer leagues—English Premier League in England, Serie A in Italy, League 1 in France, La Liga in Spain, and Bundesliga in Germany—to investigate consumer demand during the COVID-19 outbreak. European soccer leagues have played a key part in knitting the social fabric of European regions (Ritzer, 2012). Examining top leagues is meaningful for exploring sport fans' general demand along with their demand for socialization during the pandemic. Whereas in-stadium spectators' demand in England, Germany, and Italy decreased based on newly confirmed domestic COVID-19 cases and deaths, stadium attendees in Spain and France were initially not significantly affected by the pandemic. However, a lack of response to the situation cannot guarantee consistent attendance demand in stadiums. Reade and Singleton recommended that sport organizations implement more dynamic pricing strategies to maintain financial stability with an expectation of lower consumer demand—a factor that also affects secondary market ticket pricing and consumers' WTP.

The COVID-19 pandemic has not merely compromised attendance demand. Studies have mapped pandemic-induced consequences as well. Reade et al. (2021) echoed Reade and

Singleton (2021) by exploring in-stadium attendance in Belarussian Premier League (BPL) football. The authors could assess attendance during the pandemic period because BPL continued scheduled games without restrictions unlike other sport leagues in Europe and elsewhere. In the BPL, fans decided not to attend games and to instead stay home and avoid COVID-19 safety threats. Game attendance decreased significantly during the pandemic. Surprisingly, demand for BPL grew slowly despite ongoing pandemic risks. A similarly unanticipated recovery in consumer demand followed the Paris attacks in November 2015. According to Frevel and Schreyer (2020), although consumer demand decreased significantly approximately two weeks after the attacks in German Bundesliga due to the potential risk of terrorism, attendance demand resumed quickly.

In addition to the direct impact of COVID-19 on consumer demand based on attendance, a number of studies have presented suggestions for how sport organizations should handle future sport events to attract or at least maintain a certain level of attendance. Sport fans prefer to participate in sport events in their own countries (e.g., in Europe and the Middle East) when sport organizations and governing bodies revoke restrictions on attendance (Perić et al., 2021). Funahashi et al. (2022) stated that Japanese sport fans would be willing to attend sport events once health and behavioral protocols are lifted. Otherwise, fans expressed caution due to the perceived risk of COVID-19. Individuals who sensed more severe COVID-19 threats demonstrated greater sensitivity to protective measures. Alfano (2022) advocated for sport organizations to deploy advanced strategies to prevent the spread of COVID-19 upon re-opening stadiums to boost attendance demand.

As sport fans' sensitivity to the pandemic can affect their willingness to attend and pay, more abundant research is needed to clarify consumers' perceived risks of COVID-19. Previous findings about epidemics can offer helpful context. The H1N1 virus, a subtype of influenza A, was the most recent severe disease outbreak prior to COVID-19. It affected the business industry and individuals despite being less concerning than COVID-19. For example, in Taiwan, GDP decreased by approximately 1% (Chen et al., 2011). Several schools were closed worldwide (e.g., Basurto-Dávila et al., 2013; Borse et al., 2011). Gitter (2017) examined in-stadium attendance demand at baseball games: attendance decreased by about 15%–30% in Mexican League baseball based on the extent of illness reports during H1N1.

Outside the sport industry, disease outbreaks have adversely affected tourism and hospitality. The International Monetary Fund predicted a roughly 3% decline in world economic growth in 2020, which happened based on the report of World Bank Group. COVID-19 affected the global economy significantly and caused households to suffer economically. According to Haryanto (2020), 3% of the global inflation rate was predicted (i.e., 4.6% in developing countries and .5% in developed countries). The International Monetary Fund (IMF) reports that global inflation rose by 46.88% between 2020 (3.2%) and 2021 (4.7%), and by 87.23% between 2021 (4.7%) and 2022 (8.8%). Tourism demand was also heavily tempered by quarantines, suspended visa processing, and border closures in certain countries (e.g., in Europe) to mitigate pandemic-related risks.

Airline revenue declined substantially as well. The International Air Transport Association (IATA, 2020) reported that airline organizations experienced fewer passengers—a more than 50% reduction versus 2019, leading to $314 billion in losses (IATA, 2020). Roughly 80% of rooms were empty, 70% of affiliated workers were laid off, approximately 1.6 million industry staff lost their jobs, and profits were slashed by 50% versus 2019. This reduction was 9 times higher than that sustained after the 9/11 attacks. The pandemic crippled tourism demand in many countries (e.g., Jaipuria et al., 2021; Rogerson & Rogerson, 2021; Sigala, 2020; Yang et al., 2021).

COVID-19 and previous crises also affected consumer demand for tourism and leisure as typified by different preferences and behavior. Harris et al. (2022) pointed out that consumers now prefer to partake in leisure- and tourism-related activities in small groups. Consumer demand and WTP for large-group sport tickets could also be expected to decrease during the ongoing pandemic compared with previous seasons. Sport fans' consumption behavior has changed in kind. Sheth (2020) outlined new consumption habits: whereas most consumers visited certain physical places to purchase products or services prior to COVID-19, most purchase platforms became web-based during lockdowns and social distancing. Technological advances compelled various industries (e.g., work, education, and entertainment) to invest in and develop online platforms to maintain financial stability. On a related note, sport organizations need to grasp changes in consumer demand and WTP to attend in-stadium games.

Hypotheses Development

When evaluating the risk of COVID-19, it is crucial to examine five factors that may affect fans' willingness to pay. The first of these factors is risk-taking. Risk-taking is a complex behavior involving cognitive and emotional processes (Zhang et al., 2019). It requires individuals to assess the potential benefits and costs of a particular action or decision and then make a choice based on that assessment. The level of risk-taking behavior can vary widely among individuals. A number of factors, such as personality traits, previous experiences, social norms, and cultural values, can influence it. Generally, risk-taking behavior can be divided into positive and negative categories. Positive risk-taking involves engaging in behaviors that have the potential to bring about positive outcomes, such as taking on new challenges, pursuing new opportunities, and seeking new experiences. However, negative risk-taking involves engaging in behaviors that have the potential to bring about adverse outcomes, such as reckless driving, drug abuse, or gambling (Zhang et al., 2019). While risk-taking can lead to significant rewards, it can also lead to negative consequences, such as injury, financial loss, or social isolation. As such, it is important for individuals to carefully consider the potential risks and benefits of any action or decision before engaging in risk-taking behavior. Hypothesis 1 explores the relationship between risk-taking behavior and the perceived level of risk associated with the COVID-19 threats that have emerged in society.

H1 The higher one’s level of risk taking, the lower the perceived risk from COVID-19.

Perceived risk warrants a more comprehensive analysis. Weber and Milliman (1997) defined perceived risk in terms of behavior, namely risk seeking and avoidance. Specifically, perceived risk refers to an individual's subjective assessment or evaluation of the likelihood or potential harm associated with a particular activity, behavior, or situation. It is based on their perception of risks and may not always align with objective or factual risk assessments. In the context of COVID-19, the perceived risk refers to an individual's perception or assessment of the likelihood and potential consequences of contracting the virus. Although most studies on the topic in sport have been related to injuries from physical activity, work in associated industries (e.g., hospitality and tourism) has addressed the role of perceived risk in tourists' intentions to attend and to pay additional money for safer environments (e.g., Sánchez-Cañizares et al., 2021). In framing perceived risk as the potential risks of visiting specific destinations (Fuchs & Reichel, 2006), researchers have found a significant relationship between perceived risk and tourists' decision-making (e.g., Kozak et al., 2007; Sönmez & Graefe, 1998). Sánchez-Cañizares et al. (2021) contended that perceived risk significantly negatively impacts tourists' travel intentions and WTP (e.g., Lobb et al., 2007; Quintal et al., 2010), and people's risk perceptions differ. Their behavior then varies accordingly. Therefore Hypothesis 2 examines the relationship between perceived risk and risk attitude toward COVID-19.

H2 The higher the perceived risk from COVID-19, the more negative one’s attitude towards COVID-19.

As discussed, perceived risk affects consumers' willingness to attend (perceived attitude) and pay for services in the sport, leisure, and tourism industries during crises (e.g., disease outbreaks and terrorism; Floyd et al., 2004; Funahashi et al., 2022; Reade & Singleton, 2021). Sport researchers have uncovered a significant negative effect of COVID-19 on consumer demand in various leagues due to potential risks from uncertain circumstances. However, as Reade and Singleton (2021) indicated, some sport leagues have displayed a slow but notable recovery despite consistent COVID-19 cases and deaths in the community. Prior to COVID-19, related industries (e.g., tourism) featured inconsistent results regarding consumer demand based on varying degrees of perceived risk. Several researchers (e.g., Bruwer & Cohen, 2019; Fuchs & Reichel, 2006; Lepp & Gibson, 2003) determined that greater perceived risk (e.g., from terrorism, health risks, and unstable politics) could reduce travel demand: tourists preferred to avoid specific destinations due to higher perceived risk. Other scholars (e.g., Rittichainuwat, 2006; Shoemaker, 1994) observed exceptional tourist behavior around health and safety. Specifically, loyal clients who tended to visit specific places repeatedly still favored these locations despite potentially severe health and safety threats. However, as most of the literature indicates, perceived risk is anticipated to negatively influence perceived behavioral control, as shown previously (e.g., Sánchez-Cañizares et al., 2021).

Behavioral control is a concept in psychology and behavioral science that refers to an individual's perception of their ability to control or influence their behavior in a given situation.

It is an essential component of social cognitive theory, which suggests that individuals can exercise self-control and self-regulation to achieve their goals. In the context of behavior change or modification, behavioral control can be seen as a critical factor in determining whether or not a person will successfully change their behavior. If individuals believe they have the necessary skills, resources, and support to control their behavior, they are more likely to succeed in making the desired changes. On the other hand, if they perceive that their behavior is beyond their control, they may be less likely to attempt to change it. The following hypothesis is thus put forth:

H3 The higher the perceived risk from COVID-19, the lower one's perceived behavioral control over COVID-19.

Following perceived risks that indicate personal feelings and thoughts toward risk, attitude (i.e., personal beliefs about specific subjects or actions) is a crucial determinant of one's intention to execute a behavior (Ajzen, 1991; Ajzen & Fishbein, 1975). A risk attitude is a psychological trait that reflects an individual's general tendency to take risks or avoid risks in decision-making situations. It is often described as a person's willingness to take risks and can influence a wide range of behaviors and choices. People with a high-risk attitude tend to be more willing to take risks, even if there is a potential for negative consequences. They may be more likely to engage in adventurous activities or take business risks. On the other hand, people with a low-risk attitude tend to be more risk-averse, preferring to avoid situations with potential harm or loss. They may be more cautious and conservative in their decision-making.

Various factors, including personal experiences, cultural and societal norms, and individual personality traits, can influence risk attitude. It is an important factor to consider in many areas of life, such as finance, healthcare, and personal safety, as it can impact people's decisions and the outcomes they experience. Researchers have hence taken attitude as a predictor of intention (e.g., Chatzisarantis et al., 2005). In this dissertation, attitude is paired with risk from COVID-19 to reflect one's risk attitude (i.e., toward COVID-19-related risks; Hillson & Murray-Webster, 2017). People generally aim to behave rationally in ambiguous or risky situations. Individuals also typically weigh risks based on anticipated benefits and costs (Sarin & Weber, 1993). The COVID-19 pandemic has influenced tourists' risk attitudes toward specific destinations (e.g., Luo & Lam, 2020). As risk attitude predicts intention, a negative relationship has been documented between risk attitude and WTP/willingness to travel (e.g., Sánchez-Cañizares et al., 2021).

H4 The higher one’s risk attitude from COVID-19, the lower their WTP to attend NFL games amid the pandemic.

As discussed in Hypothesis 3, Ajzen (2002) explained, “perceived behavioral control … deal[s] with situations in which people may lack complete volitional control over the behavior of interest” (p. 666). This construct refers to one’s belief that they have volitional control over their behavior (Ajzen, 2002; Kang et al., 2006). When examining circumstances where people lacked control over their behavioral interests, researchers found that greater perceived control enhanced well-being (e.g., Langer, 1977; Langer et al., 1975). For example, nursing home residents’ health and longevity increased when they had complete control over their daily schedules (Rodin & Langer, 1977). Other studies (e.g., Ajzen & Madden, 1986; Conner et al., 2000; Kang et al., 2006) revealed that perceived behavioral control directly affected individuals’ actions and intentions. Therefore, although the perceived risk from COVID-19 (i.e., a unique circumstance) could decrease perceived behavioral control, NFL fans’ WTP is expected to rise if they think they have complete control over their behavioral intentions.

H5 The higher one’s perceived control behavior over sporting event participation, the higher their WTP to attend NFL games amid the pandemic.

As discussed in willingness to pay in Chapter II, willingness to pay refers to the maximum amount of money that a consumer is willing to pay for a product or service. It is often used to measure the value a consumer places on a particular item or experience. The willingness to pay can be influenced by various factors, such as the consumer's income, preferences, expectations, and perceptions of the product's quality. Understanding consumers' willingness to pay is crucial for businesses in determining the optimal pricing strategy for their products or services. Previously purchased prices can influence willingness to pay in several ways. If a consumer has previously purchased a product or service at a high price, they may be more willing to pay a similar or slightly higher price for it again. The reason could be that they have already committed to that product and may feel it is worth the price they paid. However, if a consumer has previously purchased a product or service at a low price, they may be less willing to pay a higher price for it in the future. They may perceive the higher price as unreasonable or not worth the product or service's value. Overall, previous purchase experience can shape consumers' perceptions of a product's value and influence their willingness to pay.

H6 The higher one’s spending on NFL tickets prior to COVID-19, the greater their WTP to attend NFL games amid the pandemic.

H7 The higher one’s WTP to attend NFL games during the COVID-19 pandemic, the greater their WTP for better safety services.

As discussed in Chapter I, structural equation model (SEM) was adopted in the current study to examine the hypotheses of research questions 5 and 6 (See Figure 1.1).

Chapter Summary

Over the past few decades, ticket pricing strategies have been developed as marketing and revenue generation tools. Most sport organizations have adopted demand-driven pricing strategies to price their tickets in the market. Researchers have started exploring the factors that influence consumer demand and fans' interest in the game, which can be reflected by secondary market ticket prices and the number of attendees at the venue (e.g., O'Hallarn et al., 2018; Schreyer & Ansari, 2022; Shapiro & Drayer, 2014). They have also analyzed sport fans' willingness to pay in various areas to determine the actual price range that fans would be willing to pay, taking into account various factors (Johnson et al., 2007; Kaiser et al., 2019; Popp et al., 2018). This understanding of willingness to pay can assist sport organizations in developing appropriate pricing strategies. While previous literature has considered multiple variables in pricing and willingness to pay for research, COVID-19 has yet to be investigated in this context. Even though COVID-19 is unusual, understanding ticket pricing, attendance demand, and willingness to pay concerning health risks can help sport organizations improve their marketing and pricing strategies. Furthermore, sport organizations can gain insights into their fans' demands and purchasing behavior during similar crises that may occur in the future.

CHAPTER III

METHODOLOGY

Data were collected from primary and secondary sources to investigate research questions 1 through 6 and proposed hypotheses. Primary data were obtained through survey to investigate NFL fans' willingness to pay (WTP); secondary data were used to examine secondary market ticket pricing and attendance demand. According to Hox and Boeije (2005), primary and secondary data have unique advantages that call for different approaches. Primary data allow researchers to collect accurate and relevant data that meet their specific research needs while allowing them greater control over the data collection process (e.g., Hox & Boejie). To gain accurate information from respondents, questionnaires should be simple to understand and distributed to an appropriate target sample. Secondary data can be less time-consuming and cost-effective than primary data collection. Also, secondary data can be used to address research questions even if the data were not initially collected for the study. Researchers must carefully select information, a data acquisition platform, and a sampling approach to suit their research question(s) (Hox & Boejie). Because secondary data can fulfill broad aims (i.e., not specific to a researcher's purpose), extracting data from reputable sources is essential.

Ticket Pricing and Attendance Demand: Study I

As discussed, two types of data were collected for this dissertation. First, data from a secondary data source were collected to clarify the impact of COVID-19 on ticket pricing (Q1 and Q2) and attendance demand (Q3 and Q4). Although scholars (e.g., Kemper & Breuer, 2016; Shapiro & Drayer, 2012, 2014; Shapiro et al., 2021; Watanabe & Soebbing, 2017) have identified fundamental factors that explain changes of ticket prices and the number of attendees based on consumer demand, some findings were not fully elucidated. As there are unexpected behaviors and unforeseen variables, previous results indicated that the focal model did not explain 100% of the variance in secondary market ticket pricing and attendance demand.

Sample and Data Collection

The NFL 2022 season (from September 2022 to February 2023) was referenced to address the impacts of COVID-19 cases and deaths on secondary market ticket pricing (Q1 and Q2) and attendance demand (Q3 and Q4). Although COVID-19 cases and deaths were addressed in separate research inquiries, it was deemed necessary to examine and discuss them jointly as they share similar attributes concerning the health hazards of COVID-19. Despite the modifications made to the COVID-19 protocols by the NFL and NFL Players Association before the 2022 season, safety restrictions were still in place for fans attending sporting events. As a result, examining ticket prices and the number of attendees during the 2022 season when these restrictions were lifted and fans had the freedom to choose whether or not to attend games can contribute to understanding of COVID-19's health risks.

The NFL was chosen due to its volume and demand among significant sport leagues in the United States (e.g., the MLB, NBA, and NHL). Various sources (e.g., Richter, 2022) have ranked the NFL as the country's most profitable and preferred sport league. Compared with other major sport leagues, the NFL generated $2 billion–$5 billion more in annual total revenue and had 2–5 times higher attendance on average than the MLB, NBA, and NHL in the 2022 season (Statista, 2023). All 32 teams from the NFL's four divisions (East, North, South, and West) within two leagues (American Football Conference and National Football Conference) were investigated in the current study to promote the findings' generalizability. Focusing on a few teams or certain games would hinder results regarding the pandemic's overall impact on ticket pricing and attendance.

The first and second research inquiries pertain to the impact of COVID-19 health risks on the pricing of tickets in the secondary market. A specific secondary market platform was, therefore, used: StubHub. Given secondary ticket market's dramatic growth in volume and demand, numerous web-based platforms have become available (e.g., SeatGeek, Vivid Seats, and TickPick). Specifically, StubHub was used to collect secondary market ticket prices for several reasons. First, StubHub is the NFL's official secondary market platform partner. Under this partnership, all tickets listed on the site are guaranteed by the NFL, offering high legitimacy. According to Drayer and Martin (2010), legitimacy is essential in increasing demand on secondary market platforms. Second, StubHub is one of the most successful platforms of its type. Its volume reflects heavy involvement among resellers and buyers. StubHub was valued at over $4 billion in 2019 (Sisario, 2019).

Seats were identified for the NFL's 32 stadiums. Each stadium has various seating options that are priced differently. For the current study, four sections were randomly selected from each zone based on ticket price and value. Approximately, on average, 20 sections of the entire stadium were selected per team. For example, Shapiro and Drayer (2012) demonstrated that seats in the low, middle, and high tiers are priced differently. Furthermore, secondary market vendors employ varying pricing tactics depending on the tier of the seat. High-tier seats with a higher face value often experience more frequent price changes as sellers try to avoid significant losses by adjusting prices based on consumer demand. Including sections from all stadium zones can extend the study's conclusions to a broader range of settings. Ticket prices were collected between 8:00 am and 10:00 am Eastern Time from three days prior to a game day to an actual game day to ensure consistency across observations.

According to researchers (e.g., Feehan, 2006; Tyler et al., 2017), the number of attendees can represent attendance and consumer demand in the sport industry. Therefore, for research questions 3 and 4, the number of attendees was collected from ESPN.com per game to measure attendance demand with COVID-19 health risks. The data observations for this study were gathered for two days leading up to a game day and the actual game day itself. Specifically, data sets were collected two days before the game day and the game itself. The total number of data sets collected was 77,718 from 267 out of the 272 games played in the United States, as five games were held in neutral stadiums in Europe and Mexico.

Variables

In order to comprehensively explore the influence of COVID-19 cases and deaths on the secondary market ticket prices and attendance figures, considering the established determinants of pricing and attendance is important. As a result, this study included variables that were based on previous findings as control variables. The independent and control variables of interest in this study and their data sources are described in the following subsection.

Independent Variables

Coronavirus Disease 2019 (COVID-19) Average Cases in the Last Seven Days. A continuous variable measuring the average COVID-19 cases over the last seven days for the county where the home team's stadium is located (data were gathered from the Centers for Disease Control and Prevention [CDC]).

Coronavirus Disease 2019 (COVID-19) Average Deaths in the Last Seven Days. A continuous variable measuring the average COVID-19 deaths over the last seven days for the county where the home team's stadium is located (data were gathered from the CDC).

Control Variables

To discern the impacts of COVID-19 on secondary market ticket prices and attendance demand, common determinants of ticket prices and attendance were collected to serve as control variables. Seven categories were considered (Shapiro & Drayer, 2014): 1) time-related variables, 2) game-related variables, 3) environmental variables, 4) team performance variables, 5) individual performance variables, 6) ticket-related variables, and 7) model-exclusive variables.

Time-related Variables. 1) Day of a Game (Weekday/Weekend). A variable identifying a weekday game (Monday–Friday) or a weekend game (Saturday–Sunday). Researchers have uncovered higher ticket prices and the number of attendees for weekend games than weekday games due to opportunity costs associated with buyers' daily work schedules (e.g., McDonald & Rascher, 2000). This variable was dummy coded (0 = weekday, 1 = weekend). 2) Day(s) Before a Game Day. Three time-points were considered: two days before, one day before, and on the actual game day. Because most transactions in the secondary ticket market occur during the last few days before a game (Huang & Huang, 2020; Leslie & Sorensen, 2014), it is essential to understand how time affects ticket prices. The time variable is coded as a dummy variable based on the game day. For instance, if ticket prices were obtained two days before the game day, the code for prices is 1, whereas the codes for prices collected one day before the game day and the actual game day are both 0 (indicating prices for two days before the game day). Two dummy variables were generated to account for the day(s) before the game day. 3) Game Week.

A variable identifying the week of a game based on the NFL season (e.g., Week 1, 2, 3, …, 18). The part of the season is important to teams' playoff status (Shapiro & Drayer, 2014). Games played in the latter half of a season can be regarded as more crucial, particularly for teams vying for playoff positions, compared to those played in the early and mid-season. As a result, it was anticipated that there would be an increase in ticket prices and attendance demand.

Game-related Variables. In terms of game-related factors, divisional and intra-conference games that carry playoff significance and involve divisional rivalries were associated with increased ticket prices and attendance (e.g., Shapiro & Drayer, 2014; Welki & Zlatoper, 1994). 1) Division Affiliation. A variable identifying if the opponent is in the same or a different division as the home team. This variable was dummy coded (0 = non-divisional game, 1 = divisional game). 2) Conference Affiliation. A variable identifying if the opponent is in the same or a different conference as the home team. This variable was dummy coded (0 = interconference game, 1 = intraconference game).

Environmental Variables. While numerous studies have established a statistically significant link between weather and event attendance and pricing (e.g., Kemper & Breuer, 2016), limited research has focused on examining the explanations of projected and actual weather conditions on secondary market ticket prices and the number in attendance for game days. 1) Temperature Forecast. A variable representing the expected range of temperature in Fahrenheit degrees for the day of the game, obtained from Weather.com, was recorded. 2) Precipitation Forecast. A variable measuring the forecasted precipitation rate to indicate the chance of rain for an actual game day. Data were also collected from Weather.com.

Team Performance Variables. Team performance can be evaluated based on its quality, and it is anticipated that higher ticket prices and increased demand for attendance would follow a team with a high winning percentage and the potential for postseason participation (Késenne, 2000). 1) Home Team's Post-season Status in Previous Season. A variable measuring the home team's previous post-season availability. This variable was dummy coded (0 = no, 1 = yes). Data were gathered from ESPN.com. 2) Away Team's Post-season Status in Previous Season. A variable measuring the away team's previous post-season availability. This variable was dummy coded (0 = no, 1 = yes). Data were gathered from ESPN.com. 3) Home Team's Winning Percentage. A variable measuring the home team's current winning percentage that changes each week of the season (data were gathered from ESPN.com). 4) Away Team's Winning Percentage. A variable measuring the away team's current winning percentage that changes each week of the season (data were gathered from ESPN.com).

Individual Performance Variables. The performance and visibility of star players are strongly and positively associated with attendance demand, which in turn impacts the prices of tickets on the secondary market (e.g., Jane, 2016). 1) Number of Pro-bowl Players in a Game. A variable was used to measure the number of pro-bowl players on the home and away teams, based on the previous season's roster, as the pro-bowl players for the 2022 season are only identified at the end of the regular season (data were gathered from NFLcommunications.com).

Ticket-related Variables. 1) Number of Tickets Listed for Sale. A variable measuring how many tickets were listed for sale per seller (data were gathered from StubHub). 2)

Number of Available Tickets. A variable measuring how many tickets were available at the time of observation (data were gathered from StubHub).

Uncategorized Variables. Previous literature has identified some determinants of ticket prices and attendance that remain uncategorized. However, these variables are still considered important determinants affecting secondary market ticket prices and stadium attendance, based on the findings from previous studies. 1) Home Team's City Population. A variable was included to capture the population of the home team's geographic location, with data collected from the U.S. Census. 2) Away Team's City Population. A variable was included to capture the population of the away team's geographic location, with data collected from the U.S. Census. 3) Home Team's City Income Per Capita. A variable was included to capture the income level of the home team's geographic location, with data collected from the U.S. Census. 4) Away Team's City Income Per Capita. A variable was included to capture the income level of the away team's geographic location, with data collected from the U.S. Census.

Data Analysis: Study I

In order to explore Research Questions 1-4, a linear mixed effects multilevel model, a type of hierarchical model, was considered. RStudio 2023.03.0 was employed with the lme4 R package to analyze two different outcomes (ticket price and the number of attendees). Two main factors motivated the consideration of a multilevel model in this study.

First, collected data in the current study were in a clustered and nested structure within team and game week. The multilevel model is a statistical technique for analyzing data with a nested and clustered structure (Osborne, 2000). For example, ticket prices and the number of attendees of individual games are grouped into higher-level units such as teams and game week in the current study. A multilevel model involves fitting a series of regression models, each representing a different data hierarchy level. Although covariates (i.e., predictors) could be used to explain variance at different levels (e.g., team and week), covariates also can be added at just one level without random factors. The multilevel model also allows researchers to estimate both the fixed effects (the effects of predictors that are constant across all groups) and random effects (the effects of predictors that vary across groups) on the outcome variable (Stephen & Anthony, 2002). Lastly, multilevel models can produce correct standard errors even when the assumption of independence of observations is violated by explicitly modeling the hierarchical structure of the data and accounting for the correlation among observations within groups (Krull & MacKinnon, 2001).

Another reason for choosing a multilevel model approach is the inclusion of control variables. In the multilevel model, control variables account for potential confounding factors, just as they do in standard multiple regression analysis; however, in multilevel modeling, control variables can be included that may affect the relationship between the predictor and outcome variables at each level or across levels of the data hierarchy (McCoach, 2010). Control variables can be included in the model based on previous findings of price and attendance determinants (see Chapter III, pages 66-70) and were considered in the current study. Including control variables in a multilevel model can ensure that the effects of predictor variables on the outcome variable are not spurious or confounded by other factors and can improve the accuracy of the parameter estimates and the overall model fit (e.g., Bauer & Curran, 2005; Hox et al., 2017). However, it is important to exercise caution when selecting control variables, as including too many or irrelevant variables can lead to overfitting and reduced model performance (Harrell, Jr., 2001).

To prepare the data for further analysis using a multilevel model, the data were trimmed due to their clustered structure, which involved repeated measurements for each game. For instance, game week's control variables (e.g., week 1, 2, 3, …, 18) had no variability when different ticket prices were collected for a game. To overcome this issue, Galbraith et al. (2010) recommended averaging the observations within each cluster as a common strategy to avoid or reduce the clustered structure of the data. In other words, a single measurement was obtained for each cluster (i.e., each team for each game) by calculating the mean value of the data within it, thereby simplifying the data. Using this approach, the collected data, which included 77,718 observations, were averaged for each game (N = 268). Specifically, the data-trimming process averaged multiple data points that were collected for each game. For example, I collected multiple ticket prices observations for each game. Also, 17 observations were excluded from the final data set because models can only be compared if there are no missing data for the covariates (e.g., Ibrahim et al., 2011: N = 251 games were retained for analysis). Subsequently, for answering the research questions, the ticket prices (Q1-2) and the number of attendees (Q3-4) were log-transformed to reduce the skewness of the data observations.

In order to thoroughly investigate the impact of COVID-19 health risks on ticket price and attendance demand in the NFL, it is important to consider the specific determinants of price and attendance as control variables. These determinants were discussed in the Sample and Data Collection part of this chapter (see pages 64-71) and categorized into seven categories: time-related variables, game-related variables, environmental variables, team performance variables, individual performance variables, ticket-related variables, and model-exclusive variables (Shapiro & Drayer, 2014). Specifically, 13 control variables were selected from the various investigated variables based on their consistent impact on ticket pricing and attendance in previous literature. The selected control variables were incorporated individually into the multilevel model based on their respective categories to examine how each category contributes to explaining the variance of secondary market ticket price and attendance in the NFL.

First, for time-related variables, game week (e.g., week 1, 2, 3, …, 16) and day of a game (weekday = 0; weekend = 1) were included. Although the time of a game (e.g., morning, afternoon, and night game) was considered in a couple of previous studies of attendance and ticket pricing (e.g., Shapiro & Drayer, 2014; Welki & Zlatoper, 1994), its consistent impact has not been uncovered. Accordingly, the time of a game was excluded from the model. Moreover, despite collecting data on the day before a game day to assess the influence of game time on ticket pricing, it was ultimately removed from the model during data trimming as it was deemed unsuitable for measuring attendance demand - that is, the number of attendees remained unchanged based on the day(s) preceding a game day. Specifically, according to previous studies (e.g., Sweeting, 2012), ticket prices significantly change until game time. However, the actual number in attendance only can be measured on a game day. Division affiliation (non-divisional game = 0; divisional game = 1) and conference affiliation (interconference game = 0; intraconference game = 1) were included as game-related variables.

As previously indicated in the Sample and Data Collection section (see pages 64-71), two specified performance-related categories exist. Specifically, for team performance variables, the home and away team's post-season status (did not advanced to post-season games = 0; advance to post-season games = 1) in a previous season, and the home and away team's current winning percentages were collected. Additionally, the number of 2021 pro-bowl players of the home and away teams were identified for an individual performance variable. The numbers of available tickets in the market were also collected in relation to ticket-related variables. Lastly, the distance between the home and away teams' stadiums was collected as an uncategorized variable. Home and away teams' metropolitan area income per capita and the population (i.e., number of residents) were collected based on previous studies of attendance and pricing (e.g., Rishe & Mondello, 2004; Welki & Zlatoper, 1994). However, these variables were excluded from the model as there was a lack of reasonable explanation for how income and population could effectively represent the size of a market. For environmental variables, forecasted precipitation and the highest and lowest temperatures of a game day were collected. However, the lowest forecasted temperature was eliminated due to its high collinearity with other variables in the model as indicated by the high variance inflation factor (*VIF* = 11.25). Specifically, to assess multicollinearity, I employed VIF. Control variables with a VIF value of 3 or higher were removed from the model due to potential issues with multicollinearity. Research by Mason and Perreault (1991) and Becker et al. (2015) suggests that a VIF value close to or less than 3 is acceptable.

Preliminary Analysis

After confirming dependent, independent, and control variables, statistical assumptions were checked prior to data analysis. According to previous literature (e.g., Keselman et al., 1998), approximately 10% or less of the articles reported assumptions, such as assumptions of normality and homogeneity. However, assumptions should be discussed whether assumptions are violated or not because it is an essential step to evaluate whether the underlying assumptions of a statistical model or analysis are valid and justifiable (Osborne & Waters, 2002). By acknowledging and addressing violations of assumptions, researchers can improve the quality and credibility of the research.

For the current study's multilevel model, three specific assumptions were tested according to Maas and Hox (2004): linearity, homoscedasticity, and normality. Specifically, the linearity assumption is an important assumption in many statistical analyses, which requires existence of a linear relationship between the independent variable(s) and the dependent variable(s) in the data (Poole & O'Farrell, 1971). Visualized plots (e.g., scatter and residuals) were utilized to check linearity assumption. Second, the homoscedasticity assumption should be met when conducting multilevel modeling, which is the same statistical assumption as in regression analysis that refers to the equality of variances of the residuals across all levels of the independent variable(s). In simpler terms, the homoscedasticity assumption means that the variance of the errors or residuals in a regression model is constant across all values of the predictor variable (Jarque & Bera, 1980). The scale-location plot was checked for homoscedasticity assumption. Also, homoscedasticity assumption was also checked by using the constant variance score test. Lastly, the normality assumption was considered. Assumption of normality assumes that the values of the residuals are distributed symmetrically around the mean residual, forming a bell-shaped curve. The normal distribution is a widely used statistical distribution that has several important properties, such as a well-defined mean and standard deviation, and a predictable proportion of values falling within certain ranges (Schmidt & Finan, 2018). Especially, the normality assumption is more critical for studies with small sample size (e.g., 200 or less; Israel, 1992). According to Greene (2003), studies with large sample size could be considered as meeting the normality assumption based on the Central Limit Theorem (CLT), which is a fundamental theorem in statistics that states that if a random sample of size "n" is taken from any population, then the sampling distribution of the mean of that sample will be approximately normally distributed, regardless of the shape of the population distribution, as long as the sample size is sufficiently large. The scatter plot was used to check normality assumption. If diagnostics suggested the any of assumption was violated, dependent variables would be transformed into different forms by using Log transformation or Square Root transformation (e.g., Fort & Lee, 2006). Moreover, Non-Constant Variance Score test can be used for homoscedasticity assumption, and Shapiro-Wilk test can be adopted to check normality assumption.

Descriptive Statistics

Following assumption checks, descriptive statistics were examined to oversee the trimmed data with mean, standard deviation, minimum, maximum, skew, and kurtosis values for all variables in the model. Specifically, according to Byrne (2013) and Hair et al. (2017), data can be deemed to have a normal distribution if the skewness falls within the range of -2 to 2, and the kurtosis falls within the range of -7 to 7. Outliers were also checked with scatterplots and box plots. Descriptive statistics play an essential role in summarizing and presenting data meaningfully. These statistics allow researchers to describe and analyze large datasets concisely and informally, providing insights into central tendencies, variability, and distributions of the data. Descriptive statistics help identify patterns, trends, and relationships within the data, which can inform subsequent analysis and modeling. They can also help make informed decisions and predictions based on the data. Additionally, descriptive statistics provide a basis for comparing groups and assessing the significance of observed differences or similarities. Overall, descriptive statistics are essential in the initial stages of research, where they help organize and summarize data and gain a preliminary understanding of the data before performing more advanced statistical analyses.

Multilevel Model Analysis

Following, nested data observations were tested to examine the usage of the multilevel model. I conducted an analysis of variance components to demonstrate the appropriateness of utilizing multilevel modeling as a first step in the analysis (Krull & MacKinnon, 2001). While researchers may assume that their data have a multilevel structure due to factors such as collecting information from multiple teams over a period of time, the actual variance and its placement in the model may not align with this assumption. Specifically, I investigated whether the variance in secondary market ticket prices and the number of attendees can be attributed to team and game week differences. To do so, I needed to determine the extent to which the variance in the model was accounted for by the different teams and game week. Ultimately, I aimed to determine whether the proportion of variance accounted for by team and game week level factors was significant enough to warrant utilizing a multilevel model.

To understand the necessity of multilevel modeling, I first analyzed the dependent variable's structure without any predictors (fixed or random factors) in the model using a baseline model (normal single level model), which ignores the possible clustering effect due to the nested data within teams or game week. This process allowed me to compare the multilevel model with a non-multilevel model and determine if the variance significantly improved with the multilevel structure. Next, I performed another unconditional means model (Level-1 model) considering team as a random factor without covariates. After comparing the two models (i.e., normal single level model and unconditional means model with team as a random factor), I constructed another unconditional means model (Level-1 model) by incorporating game week as a random factor to determine if significant variance in the data observations could be attributed to game week (e.g., game week 1, 2, 3, …, 18). I employed an ANOVA to assess whether the data warranted the use of a multilevel model. If the *p*-value of the test was less than .05, indicating statistical significance, I opted for the multilevel model due to its superior performance in handling nested data observations.

With the confirmation of the model, multilevel linear regression analysis (Level-2 model) was performed for Q1-2 (ticket pricing) and Q3-4 (attendance demand). Although two multilevel linear regression models had the same independent variables (number of COVID-19 cases and deaths) and control variables, there were two different outcomes based on different interests of the research questions: ticket pricing and attendance demand. As discussed, seven pricing and attendance demand determinant categories were employed to develop the model for investigating the Q1-4: 1) environmental predictors (forecasted highest temperature and precipitation); 2) predictors of time (game week and day of a game); 3) game information predictors (division and conference affiliations); 4) an individual player's performance (pro-bowl players of home and away team); 5) team performance (home and away team's post-season status in the previous year and current winning percentage of home and away team); 6) ticket information predictor (ticket availability); 7) the primary independent variables of interest (COVID-19 risk; the number of COVID-19 cases and deaths in last seven days). I excluded predictors (i.e., control variables) if the model did not show significant improvement at alpha value of .05 ($p > .05$). For example, if the model fit with environmental and time predictors did not significantly improve compared to the model fit with only environmental predictors, time-related predictors were excluded from further analysis.

Lastly, pseudo R^2 is reported with each model in Chapter IV. R^2 and pseudo-R^2 are statistical measures used to evaluate the goodness of fit of regression models. However, they differ in their interpretation and calculation. R^2 (or the coefficient of determination) is a measure of the proportion of the total variation in the dependent variable (y) that can be explained by the independent variable(s) (x) in a linear regression model. It ranges from 0 to 1, with higher values indicating a better fit between the model and the data. Instead, pseudo R^2 is a family of statistics used to measure the goodness of fit of models (Colin Cameron & Windmeijer, 1997; Vonesh et al., 1996). Moreover, typically pseudo R^2 values are reported when true R^2 cannot be calculated such as in logistic regression and in multilevel modeling. Pseudo R^2 is based on the idea of comparing the goodness of fit of the model to a null model (a model without independent variables), and it is calculated as the ratio of the reduction in residual error between the model and the null model, to the total residual error in the null model (Walker & Smith, 2016). Although the range of ordinary league squares R^2 is between 0 and 1, pseudo R^2 value does not range strictly between 0 and 1. In this study, both marginal R^2 and conditional R^2 were computed using RStudio 2023.03.0. Marginal R^2, as described by Nakagawa and Schielzeth (2013), focuses solely on the variance of the fixed effects, excluding the random effects. On the other hand, the conditional R^2 incorporates both the fixed and random effects, representing the entirety of the model.

National Football League Fans' Willingness to Pay: Study II

Along with secondary market ticket prices and the number of attendees, through this dissertation, I examined how the risk of attending a sporting event during the COVID-19 pandemic has a relationship with consumers' attitudes, perceived behavioral control, and perceived risks that potentially influence NFL fans' willingness to pay (WTP) in relation to ticket prices (Q5). Additionally, I examined the direct relationship between fans' WTP for tickets and for additional safety measures in the stadium (Q6). As discussed in Chapters I and II, seven hypotheses guided this study corresponding with research questions 5 and 6. Assessing consumers' willingness to pay (WTP) in light of primary data from a survey will significantly advance the knowledge and practice of secondary market ticket pricing and attendance demand. The results of this study might enable professional and collegiate sport organizations to better understand the importance of sport to their customers and consumers' purchase intentions amid the pandemic era. These organizations can then devise appropriate pricing and marketing strategies for future pandemics or other crises.

Respondents and Procedures

NFL fans were the target population to study COVID-19's effect on consumers' WTP to pay for a sporting event tickets. Although general sport consumers could have been chosen, NFL fans who have experience purchasing tickets for stadium experiences shed greater light on the pandemic's impacts on consumption and WTP. Most importantly, since the secondary data collection and analysis was based solely on NFL ticket prices and attendance, the survey participants must represent NFL fans. Specifically, secondary market ticket prices and the number of attendees (Q1–4) were obtained from the NFL market; Q5 and Q6 add value by concentrating on NFL fans. For Study II, 415 respondents were recruited. An online survey platform – Centiment – was used for recruitment and data acquisition following Institutional Review Board approval. Kline (2016) and Weston and Gore, Jr. (2006) stated that a minimum sample size of 200 is necessary for any SEM analysis. Moreover, a sample size of about 300 is considered large enough, as Comrey and Lee (2013) and Tabachnick and Fidell (2013) suggested. Finally, Centiment was chosen after conducting a pilot study with a diverse sample of approximately 150 respondents who exhibited different attitudes toward COVID-19 and their willingness to pay to attend an NFL game. With society gradually returning to its pre-pandemic state, a pilot study was conducted to assess the range of responses and the dependability of the survey questions.

After selecting a survey platform, the selection of respondents was based on the objective of the present study, which required individuals at least 18 years old and fans of the NFL as the primary criteria. Consent was also obtained from respondents prior to the start of the survey. The instrument included three screening questions suited to the purpose of this study (see Table 3.1 for screening questions). The screening questions aid in determining if the participants are NFL fans who support particular teams and have previously attended NFL games before the COVID-19 pandemic. Respondents who did not answer these questions correctly were not considered for data analysis. In other words, the survey was designed to remove participants who did not meet the qualifications for the study through the screening questions. Disqualified individuals were directed to the end of the survey, where they received a thank-you message for their time and effort. No incentives were given because data observations were purchased from the survey platform.

Table 3.1

Screening Questions for the Online Survey

Screening Questions
Do you identify as a National Football League (NFL) fan?
Do you have a favorite NFL team(s) for which you follow the schedule each season?
Have you attended one or more NFL games prior to the COVID-19 pandemic?

Online Survey Participants

Upon successfully passing the screening questions, demographic information was also collected from participants to gather their personal statistics. There were 10 required questions to respond to and 1 additional question which was optional, depending on the response to the 10th question. First, a gender question was asked to determine a participant’s gender identity with four response options. Responses were recorded as a numeric value: male (1), female (2), non-binary (i.e., third gender; 3), and prefer not to answer (4). Following the question on gender, participants' age was asked by selecting an age group with six response options that were also recorded as numeric values: 18-25 (1), 26-35 (2), 36-45 (3), 46-54 (4), 55-64 (5), and 65+ (6). The third demographic question was about ethnicity. Especially, six response options were provided, and responses were documented as numeric values as well: White or Caucasian (1), Black or African American (2), American Indian or Alaska Native (3), Asian (4), Native Hawaiian or Pacific Islander (5), and Other (6). Participants were allowed to have multiple answers.

Residency information was also asked of participants with a drill-down format. All 50 states were provided for options, and respondents needed to respond where they reside currently. The purpose of this question was to oversee location diversity in the survey, because if respondents are from only certain locations, the results would not be generalizable to represent all 32 NFL teams in the United States. Responses were also recorded as numeric values to determine locations that were covered by responses. Moreover, respondents were asked to indicate their level of education (Less than high school: 1; High school graduate: 2; Some college: 3; 2 year degree: 4; 4 year degree; 5: Master's degree: 6; Professional degree (e.g., J.D., M.D., Pharm.D): 7; Doctorate degree: 8) and marital status (Married: 1; Widowed: 2; Divorced: 3; Separated: 4; Never Married: 5) with responses that were numerically recorded.

Lastly, employment and current activity were asked to participants. As respondents may have more than one job or activity, multiple answers were allowed and recorded as numeric values: Self-employee (1), Wage-employee (2), Student (3), Homemaker (4), Public employee (5), Retired (6), Unemployed (7), Other (please specify; 8). In addition, unemployment status during the COVID-19 pandemic was asked to determine if COVID-19 has affected their economic status with a yes or no question that was recorded as a numeric value as well: Yes (1) and No (2). Also, as Table 3.2 shows, total household income prior to COVID-19 was asked with 12 response options, and income change was asked as well to determine if there was COVID-19 impact on household income.

Table 3.2 displays the demographic profile of the 415 participants who successfully passed the screening questions to participate in the online survey. To begin with, 52.3% of the study participants were male, 47.5% were female, and the remaining 0.2% identified as non-binary/third gender. Around half of the participants, accounting for 51.6%, fell into the age groups of 26-35 (26.3%) and 36-45 (25.3%), whereas a minor proportion of participants belonged to the 18-25 age group (7%). In addition, the majority of participants, which constitutes 79.8% of the sample, identified as White, while the second largest racial group was Black or African American, accounting for 11.8% of the sample. Out of the 42 states where participants reside, the highest percentages were from Texas (9.88%), California (8.43%), and Florida (8.19%).

Regarding educational qualifications, 38.3% of the participants held a four-year college degree, 21.2% attended some college (e.g., community college), and 15.2% held a Master's degree. In addition, 68% of participants were married, while 17.6% were never married. When asked about their current employment status, 39.3% of participants identified as wage employees, 26% as self-employed, and 16.4% as retired employees. Furthermore, although 42.7% of participants experienced unemployment during the COVID-19 pandemic, 57.3% retained their jobs. Notably, most participants (27%) fell into the income range of $100,000 to $149,000, and nearly half of the participants had an income above $70,000 (i.e., only 29.3% of participants had an income below $70,000). In addition, 53% of participants' incomes were changed due to COVID-19, and the mean income range was between $70,000 and $79,999. Compared to the average income range ($80,000 - $89,999) prior to COVID-19, the range went down due to the impact of COVID-19. Compared to previous reports (e.g., Morris, 2023), participants generally share similar characteristics with general NFL fans in the market.

Table 3.2

Demographic Profile of Participants

Demographic Characteristics (*N* = 415)	*n*	%
Gender		
Male	217	52.3
Female	197	47.5
Non-binary / third gender	1	.2
I prefer not to say	0	0
Age		
18-25	29	7
26-35	109	26.3
36-45	105	25.3
46-54	54	13
55-64	54	13
65+	64	15.4
Ethnicity		
White or Caucasian	331	79.8
Black or African American	49	11.8
American Indian or Alaska Native	3	.7
Asian	13	3.1
Native Hawaiian or Pacific Islander	1	.2
Other	14	3.4
White, American Indian or Alaskan Native, Asian	1	.3
White, Asian	1	.3
White, Native Hawaiian or Pacific Islander	1	.3
White, American Indian or Alaska Native	1	.3
Residency		
Alabama	5	1.2
Arizona	13	3.1
Arkansas	1	.2
California	35	8.4
Colorado	14	3.4
Connecticut	2	.5
Delaware	1	.2
Florida	35	8.4
Georgia	15	3.6
Hawaii	3	.7
Illinois	19	4.6
Indiana	7	1.7
Iowa	3	.7
Kansas	5	1.2
Kentucky	6	1.4
Louisiana	4	1.0
Maine	1	.2
Maryland	7	1.7

Table 3.2, *continued*

Demographic Characteristics (N = 415)	*n*	%
Residency		
Massachusetts	16	3.9
Michigan	16	3.9
Minnesota	15	3.6
Mississippi	1	.2
Missouri	4	1.0
Nebraska	1	.2
Nevada	9	2.2
New Jersey	13	3.1
New Mexico	2	.5
New York	29	7.0
North Carolina	5	1.2
North Dakota	1	.2
Ohio	26	6.3
Oklahoma	3	.7
Oregon	8	1.9
Pennsylvania	15	3.6
Rhode Island	3	.7
South Carolina	4	1.0
Tennessee	4	1.0
Texas	41	9.9
Virginia	8	1.9
Washington	7	1.7
West Virginia	2	.5
Wisconsin	6	1.4
Education		
Less than high school	0	0
High school graduate	44	10.6
Some college	88	21.2
2 year degree	46	11.1
4 year degree	159	38.3
Master's degree	63	15.2
Professional degree (e.g., J.D., M.D., Pharm.D)	7	1.7
Doctorate degree	8	1.9
Marital Status		
Married	282	68
Widowed	16	3.9
Divorced	38	9.2
Separated	6	1.4
Never Married	73	17.6

Table 3.2, *continued*

Demographic Characteristics (N = 415)	*n*	%
Employment/Current Activity		
Self-employee	108	26
Wage-employee	163	39.3
Student	5	1.2
Homemaker	12	2.9
Public employee	31	7.5
Retired	68	16.4
Unemployed	9	2.2
Other (please specify)	19	4.6
Unemployment during COVID-19		
Yes	177	42.7
No	238	57.3
Household Income prior to COVID-19?		
Less than $10,000	1	.2
$10,000 to $19,999	0	0
$20,000 to $29,999	4	1
$30,000 to $39,999	8	1.9
$40,000 to $49,999	13	3.1
$50,000 to $59,999	50	12
$60,000 to $69,999	46	11.1
$70,000 to $79,999	70	16.9
$80,000 to $89,999	28	6.7
$90,000 to $99,999	50	12
$100,000 to $149,999	112	27
$150,000 or more	33	8
Income Change due to COVID-19		
Yes	220	53
No	195	47
If yes, Changed Total Household Income?		
Less than $10,000	3	.7
$10,000 to $19,999	1	.2
$20,000 to $29,999	1	.2
$30,000 to $39,999	7	1.7
$40,000 to $49,999	9	2.2
$50,000 to $59,999	26	6.3
$60,000 to $69,999	26	6.3
$70,000 to $79,999	30	7.2
$80,000 to $89,999	15	3.6
$90,000 to $99,999	25	6.0
$100,000 to $149,999	56	13.5
$150,000 or more	21	5.1

Measurements

After collecting demographic information, questions were asked in relation to risk taking, perceived risk, risk attitude, perceived behavioral control, willingness to pay, and willingness to pay for an additional COVID-19 safety in the stadium. Prior to asking questions, instructions were provided to ensure that participants understood that they would be responding using 5- and 7-point Likert scales (see Table 3.3).

Risk Taking

In investigating the role of perceived risk in NFL fans' WTP, respondents' risk-taking propensity was considered. Risk taking involves one's attitudes towards specific activities (e.g., gambling and extreme sports; Lamb et al., 2020; Zhang et al., 2019). The General Risk Propensity Scale (GRiPS) addresses perceived risk and decision-making behaviors (e.g., Bromiley & Curley, 1992; Fox et al., 2015). Risk taking has been found to significantly affect individuals' thoughts and actions (Schonberg et al., 2011). Researchers have also emphasized the association between personal disposition (e.g., developmental stability and genetic determinants) and risk taking (Josef et al., 2016). Risk taking is situational (i.e., environmental circumstances can promote it; Scholer et al., 2010; Tversky & Kahneman, 1986). Individuals with a greater risk-taking propensity should be less concerned about COVID-19 risks. Eight items on risk taking were adopted from Zhang et al. (2019) and scored on a 5-point Likert-type scale: 1 = strongly disagree, 2 = somewhat disagree, 3 = neither agree nor disagree, 4 = somewhat agree, 5 = strongly agree. With a sample of 233 participants, Zhang et al. (2019) found acceptable internal consistency with Cronbach's alpha value of .92. Questions of the current study are related to respondents' viewpoints about risk taking behaviors and attitudes (e.g., I enjoy taking risks in most aspects of my life; I commonly make risky decisions). In the current study, Cronbach's alpha value of .94 was obtained with a sample size of 415 participants.

Perceived Risk

To investigate effects of the perceived risk of COVID-19 on NFL fans' risk-related attitudes and perceived behavioral control, six items were adopted from Conway et al. (2020) and scored on a 7-point Likert scale with ascending order: 1 = strongly disagree, 2= disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree, 7 = strongly agree. Especially, items of perceived risk ask about participants' considerations about potential risks of COVID-19 to themselves and people about whom they care (e.g., Thinking about the COVID-19 makes me feel threatened; I am worried that I or people I love will get sick from COVID-19). According to Conway et al. (2020), multiple validity tests were performed for scale development with a sample of 413 participants. As a result, Conway et al. (2020) demonstrated that scores from the scale showed high reliability with Cronbach's alpha value of .88. In the current study, a higher Cronbach's alpha value of .92 was obtained with a sample size of 415 participants.

Risk Attitude

As discussed in Chapter II, attitude can be considered a key behavior determinant related to personal beliefs (e.g., Ajzen, 1991). To measure risk attitude towards COVID-19, three items were adopted from Luo and Lam (2020) that were supported by high reliability. Especially, questions were related to participants' attitudes towards risk of COVID-19 to attend NFL games (e.g., I cannot accept going to a sporting events venue with family and friends during the COVID-19 pandemic; I will NOT eat with local friends and relatives after their participation in sporting events during the COVID-19 pandemic). The impact of risk attitude on NFL fans' WTP for a sporting event was measured in the current study with a 5-point Likert-type scale: 1 = strongly disagree, 2 = somewhat disagree, 3 = neither agree nor disagree, 4 = somewhat agree, 5 = strongly agree. Especially, questions were related to participants' attitudes towards risk of COVID-19 to attend NFL games (e.g., I cannot accept going to a sporting events venue with family and friends during the COVID-19 pandemic; I will NOT eat with local friends and relatives after their participation in sporting events during the COVID-19 pandemic).

Specifically, with the sample size of 303 participants (travelers), Luo and Lam showed a high Cronbach's alpha value of .91. Also, a range of factor loadings from Luo and Lam's study was between .63 and .93. In the current study, with the sample size of 415 participants, a similar Cronbach's alpha value of .91 was found.

Perceived Behavioral Control

To investigate the impact of perceived behavioral control on NFL fans' WTP, three items were adopted from Lam and Hsu (2006). For three items, the 7-point Likert scale was utilized: 1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree, 7 = strongly agree. All items are related to participants' attitudes toward ability to control their participation in sporting events during COVID-19 (e.g., I could easily participate in sporting events during COVID-19; I have control to participate in sporting events during COVID-19). Lam and Hsu found acceptable reliability: Cronbach's alpha value of .78 with a total of 177 participants: travelers. In the current study, higher Cronbach's alpha value of .89 with 415 participants.

Willingness to Pay and Past Spending

Two broad types of measures, direct and indirect, can be employed to evaluate consumers' WTP (Hofstetter et al., 2021). Direct measures, such as open-ended questions, as well as the Van Westendrop method for hypothetical WTP; and Becker et al.'s (2015) mechanism and an incentive-aligned assessment of the WTP range for actual WTP, can convey people's WTP for products (Anderson et al., 1992; Hofstetter et al., 2013; Steiner & Hendus, 2012). Hofstetter et al. (2021) argued that measuring hypothetical WTP has several advantages over other approaches (e.g., capturing real price sensitivity and implementation). Open-ended questions and the Van Westerndrop method have frequently been used to measure hypothetical WTP. In this dissertation I focused on NFL fans' maximum WTP to attend games based on open-ended question. Each game could generate different degrees of WTP to attend. Asking about ticket prices can clarify fans' overall intentions to pay a maximum ticket price. Respondents were also asked to indicate their average spending on NFL tickets prior to COVID-19 to determine how COVID-19 has influenced WTP in the secondary NFL ticket market.

Willingness to Pay for Higher Safety

Consumers have been required to pay pandemic surcharges in various industries amid the pandemic (i.e., hotels and restaurants): these surcharges are equal to a certain percentage of the product cost, similar to taxes. The issue of whether NFL fans are willing to pay an additional fee during the pandemic to increase stadium safety was explored. This aspect was investigated with three items scored on a 7-point scale: 1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = agree, 7 = strongly agree. Specifically, three items ask participants regarding their willingness to make additional payment for safety service in the stadium (e.g., I am willing to pay more for additional safety measures for the staff who serve me during my NFL game participation; I am willing to pay more for additional safety measures on the means of transport I use to participate in NFL games), These items were adapted from Sánchez-Cañizares et al. (2021) and scales were developed based on work by Agag et al.

(2020), Han et al. (2010), and Wei et al. (2018). The study of Sánchez-Cañizares et al. found high reliability with Cronbach’s alpha value of .92 with a total of 618 respondents of travelers. Also, scores from the adopted items were found to be reliable with Cronbach’s alpha value of .95 in the current sample, and the factor loadings in the current study’s structural model, which are reported in Chapter IV, also provided evidence of validity.

Table 3.3

Survey Rating Scale Items

Items
Risk Taking
RT1: Taking risks makes life more fun.
RT2: My friends would say that I am a risk taker.
RT3: I enjoy taking risks in most aspects of my life.
RT4: I would take a risk even if it meant I might get hurt.
RT5: Taking risks is an important part of my life.
RT6: I commonly make risky decisions.
RT7: I am a believer of taking chances.
RT8: I am attracted, rather than scared by risk.
Perceived Risk
PR1: Thinking about the COVID-19 makes me feel threatened.
PR2: I am afraid of the COVID-19.
PR3: I am NOT worried about the COVID-19.
PR4: I am worried that I or people I love will get sick from COVID-19.
PR5: I am stressed around other people because I worry, I will catch COVID-19.
PR6: I have tried hard to avoid other people because I do not want to get sick from COVID-19.
Risk Attitude
RA1: I cannot accept going to a sporting events venue with family and friends during the COVID-19 pandemic.
RA2: I cannot accept that local friends and relatives participate in sporting events during the COVID-19 pandemic.
RA3: I will NOT eat with local friends and relatives after their participation in sporting events during the COVID-19 pandemic.
Perceived Control Behavior
RCB1: I could easily participate in sporting events during COVID-19.
RCB2: I am able to participate in sporting events during COVID-19.
RCB3: I have control to participate in sporting events during COVID-19.
Willingness to Pay
How much did you pay on average for the NFL game(s) before the COVID-19 pandemic?
How much would you be willing to pay at a maximum for the NFL game during the COVID-19 pandemic?
Willingness to Pay for Safety Service
WTPS1: I am willing to pay more for additional safety measures for the staff who serve me during my NFL game participation.
WTPS2: I am willing to pay more for additional safety measures in the sport venue where I participate in NFL games.
WTPS3: I am willing to pay more for additional safety measures on the means of transport I use to participate in NFL games.

Data Analysis: Study II

As discussed in Chapter I and II in conjunction with the proposed hypotheses, structural equation modeling (SEM) was performed to examine the hypothesized relationships (Risk Taking → Perceived Risk (H1); Perceived Risk → Risk Attitude (H2); Perceived Risk → Behavioral Control (H3); Risk Attitude → WTP for Safety (H4); Perceived Behavioral Control → WTP for higher safety (H5); Previous Spending → WTP (H6); WTP for higher safety → WTP (H7)). This method can evaluate relationships among observed and latent variables in addition to uncovering the networks among variables (e.g., Hoyle, 2011; MacCallum & Austin, 2000; Rigdon, 1998). A sufficiently large sample is needed to fulfill SEM requirements. Because what constitutes a "large sample" (e.g., 200 or 300 participants; Comrey & Lee, 2013; Kline, 2011; Tabachnick & Fidell, 2013) can vary, no single calculation can determine an appropriate sample size. Suhr (2006) suggested

> a desirable goal is to have a 20:1 ratio for the number of subjects to the number of model parameters. However, a 10:1 [ratio] may be a realistic target. If the ratio is less than 5:1, the estimates may be unstable (p. 2).

As mentioned, 415 respondents were recruited for Study II of this dissertation. After data collection, the frequency of data observations was examined to understand a holistic sense of the data observations in addition to means, medians, minimum, maximum, skewness, and kurtosis of the data. SPSS version 21 was utilized for descriptive statistics. Missing data were also checked prior to model analysis (e.g., model identification, testing, and evaluation) and no missing values were shown. No missing data were obtained by requesting Centiment (i.e., selected online survey platform) not to send any surveys with missing data, which precluded ability to determine if there were any missing data.

Prior to discussing model specification in more detail, the observed indicator variables should be distinguished from the latent variables. In SEM, a latent variable is an unobserved variable inferred from a set of observed variables or indicators. An effect indicator latent variable is a latent variable that is used to explain the relationship between observed variables or indicators. It represents a common factor that influences the observed variables and reflects the effects of one or more variables on another variable in the model.

In this dissertation, the model needed to be identified using specified rules. Model identification refers to the process of determining whether the model is uniquely estimable based on the observed data (Akaike, 1974). It is an important step in SEM as it ensures that the model parameters can be estimated without ambiguity. Some alternative techniques nevertheless warrant attention. A model is identified if it can produce a unique set of estimates for the model parameters based on the available data. In other words, if the data provide enough information to estimate all of the model's parameters, the model is identified (just-identified or over-identified). The difference between the number of nonredundant elements in the variance/covariance matrix and the number of free parameters equals the degrees of freedom (*df)*. If free parameters outnumber the number of unique elements in the variance/covariance matrix of the observed data, the *df* will be negative, leading to an under-identified model. This case has no unique solution, and the information obtained is insufficient. In a just-identified model ($df = 0$), there is adequate information to derive a unique solution(s) for the free parameters but no way to test model fit. An over-identified model ($df > 0$) includes a higher number of solutions than free parameters and allows for assessment of model fit. Although there is no exact solution, various estimation options are available to find the right one.

Model estimation was carried out in the current study once the model was identified (i.e., over-identified) using Mplus version *7.11*. This step returned parameter estimates such as factor loadings and path coefficients. Parameter estimates with the smallest residuals should be selected regardless of the chosen estimation approach (e.g., maximum likelihood, generalized least squares, partial least squares, and weighted least squares). Prior research (e.g., Hoyle, 2011; Kline, 2018) deemed maximum likelihood the most favorable estimation method for SEM when all variables in the model are continuous and multivariate normally distributed. However, as most of the indicator variables in the current study were neither continuous nor multivariate normal, the standard theory maximum likelihood estimation procedure was not appropriate for the study. In this case, weighted least squares means and variance estimation (WSLMV) was used to be more suitable (Li, 2016).

The model fit was reported based on the following fit indices: chi-square statistic, root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker–Lewis index (TLI). In the current study RMSEA smaller than .06, and CFI and TLI higher than .95 were considered to indicate a good model fit (e.g., Hu & Bentler, 1999). To assess component fit, factor loadings were also considered (Kline, 2018). In SEM, factor loadings represent the correlation between each indicator variable and the latent construct. Higher factor loadings indicate a stronger relationship between the variable and the construct. Additionally, standardized residuals and factor variance can be essential information as well. Specifically, magnitude (i.e., values closer to 1) and statistical significance ($p < .05$) were considered. Standardized residuals can be used to identify areas of the model's misfit, and the latent construct's variance can be used to assess the amount of variance in the indicators accounted for by the construct. Higher factor variance indicates that the construct accounts for a more significant proportion of the variance in the indicators.

I also computed the composite reliability (CR) and average variance extracted (AVE) to evaluate the dependability and accuracy of scores related to the constructs (Kline, 2018). A CR value exceeding .7 and an AVE value greater than .5 were established in the current study as benchmarks to determine if the scores obtained on the scales were reliable (Kline, 2018). Also, McDonald’s omega was used to examine the reliability of scores on each latent variable (Dunn et al., 2014) using Mplus version *7.11* (see Appendix B). Although Cronbach's alpha is a measure of reliability commonly used in research to evaluate the internal consistency of a set of items in a scale or questionnaire, McDonald’s omega is preferred due to its robustness (e.g., Goodboy & Martin, 2020). McDonald's omega is a more robust measure than Cronbach's alpha when the items do not have equal loadings on a single factor (Hayes & Coutts, 2020; Zhang & Yuan, 2016). In contrast, Cronbach's alpha assumes that all the items are tau-equivalent and that they measure a single underlying construct. McDonald's omega is a reliability coefficient that ranges from 0 to 1, where a value of 1 indicates perfect internal consistency and a value of 0 indicates no internal consistency. In general, values of McDonald's omega above .7 are considered acceptable for most research purposes (Linzer et al., 2022), although the specific cutoff may depend on the nature of the construct being measured and the intended use of the scale.

Model Specification

After understanding theoretical practices to analyze structural equation modeling (SEM) properly, two steps of the SEM approach were adopted for this study. Step 1 is the measurement phase, and Step 2 is the structural phase.

Measurement Phase

First, the measurement phase in SEM refers to the process of measuring latent variables. As described above, latent variables are unobserved or indirectly measured variables inferred from observable indicators, such as survey items. During the measurement phase, the researcher identifies a set of indicators that are hypothesized to measure the latent variable of interest. The indicators are then measured, and the resulting data are used to estimate the measurement model: a set of equations describing the relationship between the latent variable and its indicators. The measurement model (which is a confirmatory factor analysis [CFA] model) specifies the factor loadings and also the error terms, representing the portion of the variance in each indicator not explained by the latent variable. Once the measurement model is estimated, it can be used in the next phase of SEM, which is the structural phase.

In the measurement phase, CFA was performed. In CFA, the researcher specifies a theoretical model representing the hypothesized relationships between the latent factors and the observed indicators (Klem, 2000). The model specifies the number of factors, the indicators associated with each factor, and the factor loadings that represent the strength of the relationship between each indicator and its corresponding latent factor. The model also includes error terms that capture the unexplained variance in each indicator. The CFA model is then tested against the data to determine how well the observed data fit the theoretical model. In the current study this was done using the aforementioned goodness-of-fit indices: the chi-square test, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker–Lewis index (TLI).

Structural Phase

After establishing an acceptable measurement model, the next step was to conduct analyses to evaluate the goodness of fit of the structural model. In the structural phase, the relationships between latent variables are modeled, along with the relationships between the latent variables and any observed variables. The measurement model provides the foundation for the structural model, specifying the relationship between the latent variables and their observed indicators. The adequacy of the full structural model was evaluated using the same goodness-of-fit indices and cutoff values used to test the CFA model, including RMSEA, TLI, and CFI. If the assessment revealed an unsatisfactory fit overall, it suggests that the proposed model does not adequately explain the relationships among the observed variables (Anderson & Gerbing, 1988).

Chapter Summary

To sum up, this study utilized quantitative methods, specifically multilevel modeling and structural equation modeling (SEM). The study aimed to examine the health risks of COVID-19 on secondary ticket prices and attendance demand by collecting the of COVID-19 cases and deaths in a seven-day period as the main variables of interest. For the dependent variables in Study I, secondary market ticket prices were obtained from StubHub, while attendance figures were sourced from ESPN.com for NFL games in the 2022 season. Given the clustered structure of the data based on team, multilevel modeling was used to investigate the impact of COVID-19. Prior to the analysis using multilevel model, data were averaged per game to partially address the issue of clustered and nested data due to repeated measures across team. Furthermore, to fully examine the effect of COVID-19, previous price and attendance determinants were gathered as control variables.

Furthermore, apart from conducting secondary data analysis using multilevel model, this study also utilized SEM to explore the impact of COVID-19 on the willingness of NFL fans to pay for attending games. The target population for the study comprised individuals aged at least 18 years who self-identified as NFL fans and had previously attended NFL games prior to the COVID-19 pandemic. To recruit the sample, the study utilized quota sampling, and participants were sourced from the Centiment panel of U.S. residents who voluntarily completed an online survey. The online survey questionnaire consisted of screening questions, demographic questions, and various items measuring constructs such as risk-taking, perceived risk, risk attitude, perceived behavioral control, and willingness to pay. Using the M*plus* version 7.11 software, the study analyzed a SEM to examine the association between COVID-19 and the willingness of fans to pay for attending NFL games during the pandemic, as well as their willingness to pay for additional safety measures to prevent COVID-19 transmission in stadiums. In accordance with the established methodology, Chapter IV presents the findings of the study, while Chapter V offers a comprehensive discussion of the results and outlines future research directions considering the (de)limitations inherent in the current study.

CHAPTER IV

RESULTS

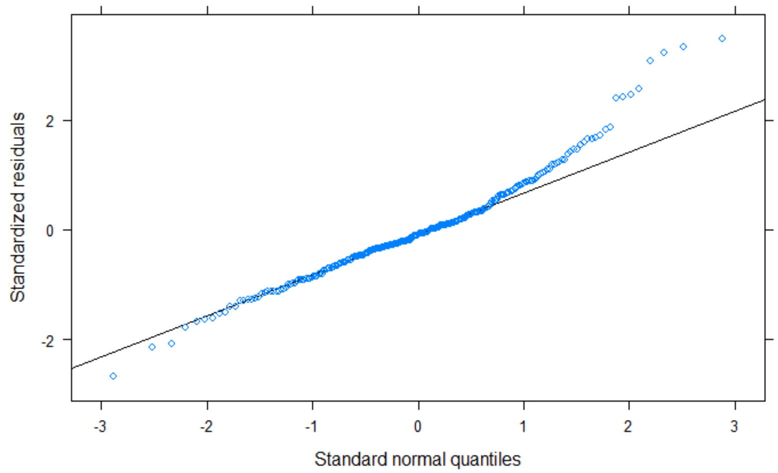
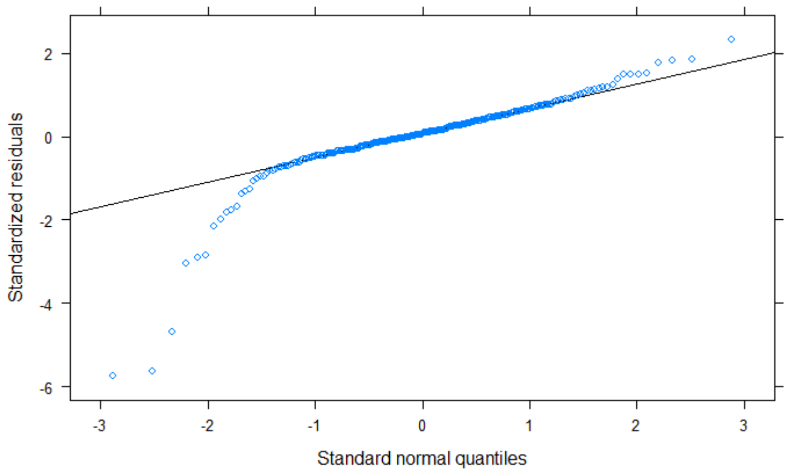
This chapter presents the outcomes of statistical tests that were conducted to address research questions 1 through 6 (Q1-6), along with their associated hypotheses. The initial section of the chapter offers a comprehensive account of the preliminary analysis and descriptive statistics of the secondary data observations for Q1-4. The subsequent section presents the findings of multilevel regression analysis. For Q5 and Q6, the chapter reports on the results of the confirmatory factor analysis (CFA) and structural equation modeling (SEM) analysis, which examined the direct effects of latent variables in the hypothesized model based on survey responses collected in Study II.

Preliminary Analysis

First, as discussed in Chapter III, I checked three assumptions for the multilevel linear regression model. The linearity assumption was met, as indicated by the scatterplot of the residuals against the predicted values from the regression mode (RStudio 2023.03.0 was used; RStudio Team, 2020). In other words, the relationship between the independent variables and the dependent variable can be described by a straight line, and the linear regression model is appropriate for the data. Also, I checked the assumption of homoscedasticity by using the constant variance score test. Tests showed that there is no evidence of non-constant variance in ticket pricing model (p = .78) and number of attendees model (p = .48): the assumption of homoscedasticity was met. Lastly, the normality assumption was checked using the plots of the residuals (see Figure 4.1) to overview the dispersion of the data observations for both log-transformed ticket prices and log-transformed number of attendees. Although most data observations appeared to meet the assumption of normality, several existences of outliers did not lie well along the line that represents the expected quantiles of a perfectly normal distribution: normality assumption was not met.

Figure 4.1

Normality Test Using the Plots of the Residuals

Log-Transformed Ticket Pricing	Log-Transformed Number of Attendees
	

After checking the assumptions with transformed variables (log transformation; Fort & Lee, 2006), I decided to analyze a multilevel model with non-normal data distributions for the current study for the following reasons. Previous literature (e.g., Gelman & Hill, 2006; Schielzeth et al., 2020) suggests that multilevel modeling can be robust to violations of distributional assumptions, which are often violated in real-world datasets. Moreover, as discussed in Chapter III, violations of the normality assumption may become less critical or even negligible with a large enough sample size (usually more than 200 sample size; Greene, 2003). The Central Limit Theorem (CLT) states that, under certain conditions, the sampling distribution of the mean of a sufficiently large sample from any population will be approximately normally distributed, regardless of the underlying distribution of the population. CLT also applies to any parameter estimate that can be calculated from a sample, not just means Also, data could be considered as normal if the value of skewness lies between -2 to 2 and the value of kurtosis lies between -7 to 7 (Byrne, 2013; Hair et al., 2017). In the current study, values of skewness (-.06) and kurtosis (3.27) for ticket prices are within acceptable range, and values of skewness (.38) and kurtosis (5.92) for the number of attendees also lie in the proper range.

Lastly, I decided to keep outliers in the data observations because outliers can provide valuable information in some cases (Aggarwal, 2017). Outliers are observations significantly different from other observations in the dataset, representing extreme values in the current study. Specifically, each NFL stadium has a different capacity (ranging from 61,500 to 82,500 seats; some stadiums can be considered outliers), and each game's demand varied by different determinants. Therefore, data observations without outliers would not be able to represent the ticket prices and attendance demand of entire NFL teams accurately.

Descriptive Statistics: Secondary Data Observations

Table 4.1 presents descriptive statistics and acronyms for all variables in the multilevel modeling for Q1 through Q4.

Table 4.1

Variables and Descriptive Statistics

Variables	*N*	*M*	*SD*	*MIN*	*MAX*
ln(TP): Logarithm of ticket price	251	5.45	.56	3.59	7.01
TP: Ticket Price	251	273.66	167.85	36.24	1,110.50
ln(ATT): Logarithm of number of attendances	250	11.14	.10	10.79	11.45
ATT: Number of attendances	250	69339.13	6849.71	48423.00	93843.00
CVDC: Covid-19 average cases in 7 days	251	259.85	297.33	.00	1688.33
CVDD: Covid-19 average deaths in 7 days	251	2.48	3.22	.00	16.00
HTP: Forecasted highest temperature	251	61.09	18.20	4.00	103.00
PRCP: Forecasted precipitation	251	18.85	24.89	.00	100.00
HPOF: Home team’s playoff status in previous season (0 = no, 1 = yes)	251	.44	.50	.00	1.00
APOF: Away team’s playoff status in previous season (0 = no, 1 = yes)	251	.43	.50	.00	1.00
HTW: Home team’s current winning percentage	251	50.14	23.67	.00	100.00
ATW: Away team’s current winning percentage	251	50.10	23.00	.00	100.00
STAR: Home and away teams’ number of pro-bowl players in previous season	251	5.52	2.86	.00	13.00
DIV: Division Affiliation (0 = non-divisional game, 1 = divisional game)	251	.35	.48	.00	1.00
CONF: Conference Affiliation (0 = interconference game, 1 = intraconference game)	251	.70	.46	.00	1.00
GW: Game week	251	10.04	5.04	2.00	18.00
WK: Day of a game (0 = weekday, 1 = weekend)	251	.87	.34	.00	1.00
AVAIL: Number of available tickets in the market	251	103.52	88.21	14.67	642.67

First, as reported in Table 4.1, the average price of tickets in terms of actual dollars is $273.66 (*SD* = 167.85). The maximum price recorded was $1,110.50 for a game played between the Pittsburgh Steelers and the New England Patriots, while the minimum price was $36.24 for a game played between the Cleveland Browns and the New Orleans Saints. When considering the actual dollar value of ticket prices, it is important to note that there may be significant variation among the average prices, as shown by the relatively large standard deviation of approximately $168. A wide range of ticket prices is present because the ticket prices were collected from multiple sections and teams, which may represent different seat levels within the stadium.

In addition, the study examined another dependent variable (Q3-4): the number of attendees for NFL games during the 2022 season. The mean attendance was approximately 69,339 (*SD* = 6,849.71). The maximum number of attendees was recorded at the AT&T Stadium (i.e., Dallas Cowboy's stadium), where 93,843 people attended a game. In contrast, the minimum number of attendees was recorded at a Chicago Bears game, with 48,423 people in attendance. Large disparities in attendance across the teams could be one of good reasons to utilize multilevel modeling to account for the clustering effect of team. Attendance between Cincinnati Bengals and Buffalo Bills (January 2, 2023) was not recorded as the game was postponed and not resumed due to a significant injury sustained by Bills safety Damar Hamlin. Research questions 1 and 4 investigated two independent variables related to the number of COVID-19 cases and deaths with the following two dependent variables. The first independent variable is the number of COVID-19 cases in 7 days, with a minimum of 0 cases, a maximum of 1,688 cases, and a mean of 259.85 cases (*SD* = 297.33). The second dependent variable is the number of COVID-19 deaths during the 2022 NFL season in 7 days, with a mean of two to three deaths (*SD* = 3.2), a maximum of 16 deaths, and a minimum of 0 death.

The study focused on environmental-related variables as control variables and investigated them in detail. Specifically, the forecasted highest temperature on game day had a mean of 61.09°F (*SD* = 18.20), while the average forecasted precipitation rate was 18.85% (*SD* = 24.89). To account for team performance as another control variable, approximately 44% (*SD* = .5) of home and away teams in the collected games had advanced to the playoffs in the previous season. Additionally, the study found that a similar average current winning percentage of the home team was 50.14% (*SD* = 23.67), while that of the away team was 50.10% (*SD* = 23.00). The study also measured individual performance based on the number of pro-bowl players. The results indicate that approximately five to six pro-bowl players were presented in each game from home and away teams. In terms of game-related variables, 65% (*SD* = .48%) of the games were divisional games. Around 70% of games were intraconference (*SD* = .46%). In terms of time-related variables around 90% (*SD* = .34) of games were played on weekends, and Sunday in particular. Lastly, on average, 104 tickets (*SD* = 88.21) were available from two days before the game day until the actual game day, with the maximum number of tickets available being 643 and the minimum being 15.

Results of Multilevel Modeling

To approach Q1 (After accounting for previous findings of price determinants, does number of COVID-19 cases explain NFL secondary market ticket price?); Q2 (After accounting for previous findings of price determinants, does number of COVID-19 deaths explain NFL secondary market ticket price?); Q3 (After accounting for previous findings of price determinants, does number of COVID-19 cases explain NFL in-stadium attendance demand?); and Q4 (After accounting for previous findings of price determinants, does number of COVID-

19 deaths explain NFL in-stadium attendance?), the study used multilevel model analysis to evaluate the prediction of ticket prices and attendance demand.

Pricing and attendance determinant variables included for analysis: COVID-19 risk (CVDC: Covid-19 cases in 7 days; CVDD: Covid-19 deaths in 7 days); time-related determinants (GW: Game week; WK: Day of a game); game-related factors (DIV: Division affiliation; CONF: Conference affiliation); environmental (HTP: Forecasted highest temperature; PRCP: Forecasted precipitation); team performance (HPOF: Home team's playoff status in previous season; APOF: Away team's playoff status in previous season; HTW: Home team's current winning percentage; ATW: Away team's current winning percentage); Individual performance (STAR: Number of star players in a game from home and away teams); and Ticket-related factors (AVAIL: Number of available tickets in the market).

First, the unconditional means model was identified as described in Chapter III. In multilevel modeling, an unconditional means model includes only the outcome variable (Enders & Tofighi, 2007). The unconditional means model provides a first level of model against which to compare models that include predictor variables (e.g., weather, team performance, and individual performance). By estimating the variance components of the outcome variable at each level of the hierarchy without predictor variables, the unconditional means model can help assess the importance of including predictors in subsequent models (Enders & Tofighi, 2007). I developed an unconditional means model with a random intercept for the team as the multilevel factor in the model (random factor). Without predictors, the model summary provided random effects with an intercept. The results indicated that 32.61% of the variance in the secondary market ticket prices could be attributed to differences between the teams. By utilizing analysis of variance (ANOVA) to compare the normal single level model (i.e., a model without predictors, random, and fixed factors) and the unconditional means model (team as a random factor), I found that the unconditional means model (Level-1 model) with team as a random factor was recommended to use with the collected data by using ANOVA test ($p < .05$). In other words, there was a significant amount of variance in ticket prices based on the team.

Following the same process, the results revealed that game week accounted for 4.86% of the variance. However, when I compared the unconditional means model with a random intercept for the game week to the normal single level model, the results indicated that the unconditional means model with game week did not necessarily perform better than the normal single level model by using ANOVA test ($p > .05$). Therefore, the Level-1 model with consideration of the team was determined to be adopted to analyze further how COVID-19 health risks explain secondary market ticket prices. A Level-1 model with the team was also selected to analyze research questions 3 and 4 further, for which predictors were included in the Level-2 model.

When the number of attendees was used as the dependent variable, the results showed that the team accounted for 81.28% of the variance. Additionally, the Level-1 team model for attendance accounted for significantly more variance than the normal single level model, indicating that a significant amount of the variances in the dataset was attributable to the team by using ANOVA test ($p < .05$). However, when another unconditional means model (Level-1 model) with game week was constructed, it did not perform significantly better than the normal single level model, as determined through an ANOVA test ($p > .05$). Therefore, the same Level-1 model with the team as a random factor was adopted for research questions 1 through 4.

Once the unconditional means model (Level-1 model) was estimated, I investigated conditional models (Level-2), which included predictors or covariates to explain differences in ticket price and number of attendees. By comparing the fit of the unconditional means and conditional models, I assessed the degree to which the predictors accounted for variability in the outcome variable. Especially, as discussed in Chapter III, I excluded predictors that were considered during the model-building process but did not improve the model fit to distinguish them from the predictors that did help improve the model fit. I first tested the two-level model (Level-2; multilevel factor is team) with weather-related predictors. The model included the forecasted highest temperature (HTP). The results show that there is a significant positive association between HTP and ticket price ($\beta = .01$; $p < .05$). Also, compared to the unconditional means model (Level-1 model), the Level-2 model with HTP provided a statistically significant improvement in model fit ($R^2_{Marg} = .03$, $R^2_{Cond} = .35$, $p < .05$). However, forecasted precipitation (PRCP) was excluded from the model due to no statistically significant contribution to the model improvement ($p = .78$). For the next step, time-related predictors were considered: game week (GW) and day of a game (WK). Although both predictors were frequently used as control variables in previous literature (e.g., Shapiro & Drayer, 2014; Shapiro et al., 2021), the model fit did not improve by adding time-related predictors: GW ($p = .84$) and WK ($p = .47$). Moreover, game-related variables were excluded from the model due to no significant improvement of the model fit: division affiliation (DIV; $p = .64$) and conference affiliation (CONF; $p = .71$).

Following time and game-related predictors, team performance predictors were added to the Level-2 model (see Table 4.2). Specifically, the results of ANOVA suggest that the Level-2 model with team performance variables is significantly improved compared to the model with forecasted highest temperature ($R^2_{Marg} = .26$, $R^2_{Cond} = .50$, $p < .05$). Although all team performance predictors significantly improved the model, individual performance (number of pro-bowl players in a game; STAR) did not have a significant contribution to model development (p = .81). Therefore, STAR was excluded from the model. With team performance predictors, a ticket-related predictor (number of available tickets; AVAIL) was included in the model, which contributed to significant improvement of model (R^2_{Marg} = .32, R^2_{Cond} = .66, $p < .05$). Lastly, COVID-19 cases and death (i.e., independent variables) were added as health risk-related predictors in the Level-2 model. The results show the model improved significantly when adding the COVID-19 related variables (R^2_{Marg} = .37, R^2_{Cond} = .73, $p < .05$). Also, when COVID-19 death had a significant negative relationship with ticket prices (β = -.04; $p < .01$), COVID-19 cases did not have a significant relationship with ticket prices (see Table 4.2). In addition to COVID-19 deaths, away team's playoff status in previous season, home and away teams' current winning percentages, and ticket availability significantly explained secondary market ticket prices in the NFL.

Table 4.2

Multilevel Regression Model Analysis for Secondary Market Ticket Price

Parameters	Unconditional Means Model (Level-1 Model)	Level-2 Model
Fixed effects		
Intercept	5.45 (.06)**	4.84 (.17)**
HTP	-	.00 (.00)
HPOF	-	.28 (.15)
APOF	-	.20 (.05)**
HTW	-	.01 (.001)**
ATW	-	.002 (.001)*
AVAIL	-	-.002 (.0004)**
CVDC	-	-.00 (.00)
CVDD	-	-.04 (.01)**
Random effects		
Residual	.22 (.46)	.12 (.35)
Intercept	.10 (.32)	.16 (.40)
Model summary		
R^2 Marg.	-	.37
R^2 Cond.	-	.73

Note. Marginal R^2 (R^2 Marg.) pertains to the variance that is accounted for by the fixed factors; Conditional R^2 (R^2 Cond.) pertains to the variance explained by both the fixed and random factors. Parentheses contain standard errors of parameter estimate. HTP = forecasted highest temperature; HPOF = home team's playoff status in previous season (0 = no, 1 = yes); APOF = away team's playoff status in previous season (0 = no, 1 = yes); HTW = home team's current winning percentage; ATW: away team's current winning percentage; AVAIL = number of available tickets in the market; CVDC: Covid-19 average cases in 7 days; CVDD: Covid-19 average deaths in 7 days.
*$p < .05$, **$p < .01$

As discussed in Chapter III, the same procedure was implemented for attendance demand. The unconditional means model (Level-1 model) results showed statistically significant variance in the number of attendees across teams ($p < .05$). However, another unconditional means model with game week as a random factor did not show significant improvement compared to the normal single level model that does not include random and fixed factor and covariate. Therefore, an unconditional means model with team as a random factor was confirmed as the starting model of attendance demand.

Next, I added predictors (i.e., attendance demand determinants) to the unconditional means model to specify the Level-2 model. First, weather-related predictors were added. However, compared to the unconditional means model, there was no significant improvement in the model with HTP and PRCP (p = .51). Additionally, the model fit was not improved with the inclusion of time-related predictors, such as GW (p = .68) and WK (p = .30). With the same order of multilevel model analysis used for analysis of the ticket price, game related variables were added in the Level-1 model. The results showed a significant model improvement with DIV (divisional affiliation) and CONF (conference affiliation) compared to the unconditional means model (R^2_{Marg} = .01, R^2_{Cond} = .82, p < .05). Also, there was a significant positive relationship between DIV and the number of fans in attendance indicating that attendance demand increased when the home team played a divisional game (β = .02; p < .01). In addition, a significant negative relationship between CONF and attendance demand was found that indicates more fans attended interconference game compared to intraconference game (β = -.01; p < .05).

In consideration of team performance, the away team's playoff availability in the previous season (APOF) and home team's current winning percentage (HTW) were included in the Level-2 model. The results of ANOVA confirmed that the Level-2 model was significantly improved compared to the Level-2 model with DIV and CONF (R^2_{Marg} = .02, R^2_{Cond} = .83, p < .05). There is a significant positive relationship between APOF and attendance demand (β = .02; p < .01), indicating more fans would like to attend a game against an opponent who was eligible to advance to the playoffs in the previous season. However, the rest of the team performance-related predictors (HTW, HPOF, and ATW) were not retained in the model due to limited contribution and no significant relationships with the number in attendance. When APO and HTW, the team performance predictors, were in the model, the number of star players did not contribute to improving the model fit of attendance demand (*p* = .65). In other words, unlike previous findings, attendance demand in the current study was not found to increase with more pro-bowl players in a game.

Regarding the ticket-related variable, the number of available tickets (AVAIL) was considered in the Level-2 model. Comparing the model with DIV, CONF, APO, and HTW, the results of ANOVA suggest adding AVAIL improved the fit ($R^2_{Marg} = .03$, $R^2_{Cond} = .85$, $p < .05$). Moreover, there is a significant negative relationship between AVAIL and attendance demand ($\beta = -.0001$; $p < .01$). Specifically, when more tickets were available, attendance demand decreased. Lastly, COVID-19 health-related risks were considered. There was a statistically significant model contribution of COVID-19 cases to the model ($R^2_{Marg} = .05$, $R^2_{Cond} = .85$, $p < .05$). Specifically, less attendance demand occurred with an increasing number of COVID-19 cases ($\beta = -.0001$; $p < .01$). However, COVID-19 deaths did not improve model fit regarding number of attendees ($p = .29$). Therefore, COVID-19 deaths were removed from the final model.

Table 4.3

Multilevel Regression Model Analysis for the Number of Attendees

Parameters	Unconditional Means Model (Level-1 Model)	Level-2 Model
Fixed effects		
Intercept	11.14 (.02)**	11.15 (.02)**
DIV	-	.02 (.01)
CONF	-	-.01 (.01)
APOF	-	.01 (.01)**
AVAIL	-	.0001 (.00004)**
CVDC	-	.00004 (.00001)*
Random effects		
Residual	.002 (.04)	.001 (.04)
Intercept	.01 (.09)	.01 (.09)
Model summary		
R^2 Marg.	-	.05
R^2 Cond.	-	.85

Note. Marginal R^2 (R^2 Marg.) pertains to the variance that is accounted for by the fixed factors; Conditional R^2 (R^2 Cond.) pertains to the variance explained by both the fixed and random factors. Parentheses contains standard errors of parameter estimate. DIV: division affiliation (0 = non-divisional game, 1 = divisional game); CONF: conference affiliation (0 = interconference game, 1 = intraconference game); APOF = away team's playoff status in previous season (0 = no, 1 = yes); AVAIL = number of available tickets in the market; CVDC: Covid-19 average cases in 7 days

$*p < .05$, $**p < .01$

Results of Confirmatory Factor Analysis

First, before examining the structural equation model (SEM) in the current study, I conducted an overall confirmatory factor analysis (CFA) to help evaluate the validity and reliability of the measurement model. CFA allows us to examine the extent to which the items are related, which can help us identify if the items are measuring the same underlying construct or multiple constructs (Bandalos & Finney, 2018; Kline, 2018)

After running CFA with the hypothesized model, the observed data were not considered to fit the theoretical model based on values of RMSEA, CFI, and TLI. Specifically, although the value of CFI (.96) and TLI (.95) could be considered acceptable, RMSEA (.10) was not acceptable for model fit. Therefore, to improve the model fit, an item from Perceived Risk was removed for further analysis due to high modification indices: question 3 of perceived risk (PR3) measurement, which stated “I am NOT worried about the COVID-19.” A high modification index suggests a specific change to the model that could significantly improve the model fit (Kaplan, 1989). Factor loading (.33) and R^2 (.11) of PR3 were considerably low. Moreover, participants might not have been careful about the word “NOT” in the question.

With the exclusion of PR3 from the model, the fit indices based on the modified model were examined to determine changes in the model fit. As a result, the model fit improved to an acceptable range, $\chi 2$ (df) = 758.03 (244), $p < .001$, CFI = .98, TLI = .98, RMSEA = .07, 90% CI for RMSEA [.07, .08]. The chi-square test was statistically significant, indicating a lack of perfect fit between the model and the observed data. However, this result should be interpreted with caution as the chi-square test is known to be sensitive to sample size (Siddiqui, 2013). The CFI and TLI were above the recommended threshold of .95, indicating a good fit. The RMSEA was below .08, indicating a marginally acceptable fit.

Additionally, by analyzing the correlation matrix among the latent variables in the study, I was able to identify potential issues, such as multicollinearity, which could affect the stability and accuracy of the estimates (see Table 4.4). Based on the correlation analysis, the highest correlation was found between Perceived Risk and Risk Attitude ($r = .74$, $p < .01$). The weakest significant correlation was found between Perceived Risk and WTP ($r = -.12$, $p < .05$). Lastly, there is no statistically significant correlation between NFL fans' prior ticket spending and any other variables.

Table 4.4

Correlations among the Latent Variables

Latent variable	(*N* = 415)								
	M	*SD*	1	2	3	4	5	6	7
1. Risk Taking	3.2	1.02	1						
2. Perceived Risk	4.00	1.69	.20**	1					
3. Risk Attitude	2.84	1.28	.22**	.74**	1				
4. Perceived Behavioral Control	4.63	1.61	.34**	-.18**	-.29**	1			
5. Past Spending	4.75	.82	.05	-.01	-.06	-.05	1		
6. WTP	4.71	1.02	.14**	-.12*	-.19**	.15**	.64**	1	
7. WTP for Additional Safety	4.56	1.79	.30**	.58**	.52**	-.04	.04	.06	1

After examining the correlations among latent variables, reliability estimation was performed. Reliability estimation is crucial because it helps assess the consistency and stability of the scores from the observed variables used in the model. Specifically, reliability estimates evaluate whether the observed variables consistently measure the underlying constructs they intend to measure. Also, reliability estimation is important because if the observed variables are unreliable, the measurement model will not accurately reflect the underlying theoretical constructs, even though one of the well-known advantages of structural equation modeling is its ability to account for measurement error (Stephenson & Holbert, 2003). The results obtained from SEM will be unreliable and invalid (Petrescu, 2013). Therefore, reliability estimation helps improve the ability of the SEM model to provide accurate estimates of the relationships among the latent variables. In this study, McDonald’s omega was examined for reliability estimation. Generally, a McDonald’s omega value of .70 or higher is considered acceptable for research purposes (Linzer et al., 2022). The reliability estimates indicate that Risk Taking, Perceived Risk, Risk Attitude, Perceived Control Behavior, and Willingness to Pay for Additional Safety demonstrate exceptional reliability ($\omega > .9$).

Table 4.5

Reliability Estimates

Constructs/Items	ω
Risk Taking	.94
RT1: Taking risks makes life more fun.	
RT2: My friends would say that I am a risk taker.	
RT3: I enjoy taking risks in most aspects of my life.	
RT4: I would take a risk even if it meant I might get hurt.	
RT5: Taking risks is an important part of my life.	
RT6: I commonly make risky decisions.	
RT7: I am a believer of taking chances.	
RT8: I am attracted, rather than scared by risk.	
Perceived Risk	.90
PR1: Thinking about the COVID-19 makes me feel threatened.	
PR2: I am afraid of the COVID-19.	
PR3: I am NOT worried about the COVID-19.	
PR4: I am worried that I or people I love will get sick from COVID-19.	
PR5: I am stressed around other people because I worry, I will catch COVID-19.	
PR6: I have tried hard to avoid other people because I do not want to get sick from COVID-19.	
Risk Attitude	.90
RA1: I cannot accept going to a sporting events venue with family and friends during the COVID-19 pandemic.	
RA2: I cannot accept that local friends and relatives participate in sporting events during the COVID-19 pandemic.	
RA3: I will NOT eat with local friends and relatives after their participation in sporting events during the COVID-19 pandemic.	
Perceived Control Behavior	.90
RCB1: I could easily participate in sporting events during COVID-19.	
RCB2: I am able to participate in sporting events during COVID-19.	
RCB3: I have control to participate in sporting events during COVID-19.	
Willingness to Pay	
How much did you pay on average for the NFL game(s) before the COVID-19 pandemic?	
How much would you be willing to pay at a maximum for the NFL game during the COVID-19 pandemic?	
Willingness to Pay for Safety Service	.94
WTPS1: I am willing to pay more for additional safety measures for the staff who serve me during my NFL game participation.	
WTPS2: I am willing to pay more for additional safety measures in the sport venue where I participate in NFL games.	
WTPS3: I am willing to pay more for additional safety measures on the means of transport I use to participate in NFL games.	

Table 4.6 displays the assessment of the Confirmatory Factor Analysis (CFA) model for its component fit. CFA is a statistical technique used to evaluate the extent to which the items or variables in a measurement model are related to the latent factors they are intended to measure. Component fit refers to how well the items or indicators of a factor model align with the theoretical construct they are supposed to measure. The standardized factor loadings in the model were both practically significant ($\lambda > .5$) and statistically significant ($p < .05$). All constructs demonstrated convergent validity, with their Average Variance Extracted (AVE) values ranging from .75 to .89 and their Construct Reliability (CR) values above .92, which exceeds the recommended cut-off criteria of .5 for AVE (Fornell & Larcker, 1981; Hair et al., 2017) and .7 for CR (Tentama & Anindita, 2020).

Table 4.6

Component Fit Analysis

	λ	AVE	CR
Risk Taking		.73	.96
RT1	.85		
RT2	.87		
RT3	.89		
RT4	.82		
RT5	.86		
RT6	.87		
RT7	.80		
RT8	.86		
Perceived Risk		.75	.94
PR1	.88		
PR2	.90		
PR4	.78		
PR5	.91		
PR6	.86		
Risk Attitude		.80	.92
RA1	.89		
RA2	.91		
RA3	.89		
Willingness to Pay for Safety Service		.89	.96
WTPS1	.96		
WTPS2	.94		
WTPS3	.94		

Notes: λ = standardized factor loadings, AVE = average variance extracted, CR = construct reliability

Results of Structural Equation Modeling Analysis

After achieving acceptable results of CFA, the hypothesized structured model (see Figure 1.1) was tested to determine whether it fits the data well. Then, the path coefficients were examined with respect to their statistical significance, direction, and magnitude, as outlined by Kline (2016). However, the modified model was not identified. Therefore, it was necessary to reassess the study's proposed model and hypotheses based on the purpose of this study. Specifically, the proposed model was reviewed and subsequently modified by changing the order of willingness to pay (WTP) and WTP for higher safety, as illustrated in Figure 4.2. This change was made for the following reason. I aimed to explore fans' behavior, attitudes, feelings, and thoughts on COVID-19, and the WTP for higher safety variable was included to reflect NFL fans' perceptions of COVID-19 risks. Therefore, it was essential to ensure that WTP for higher safety had a direct relationship with risk attitude and perceived control behavior and that WTP for tickets was considered an endogenous variable, meaning it depends on other variables (COVID-19 risks) in the model. Based on this revised model and a better understanding of its limitations, three hypotheses were redefined (H4, H5, and H7):

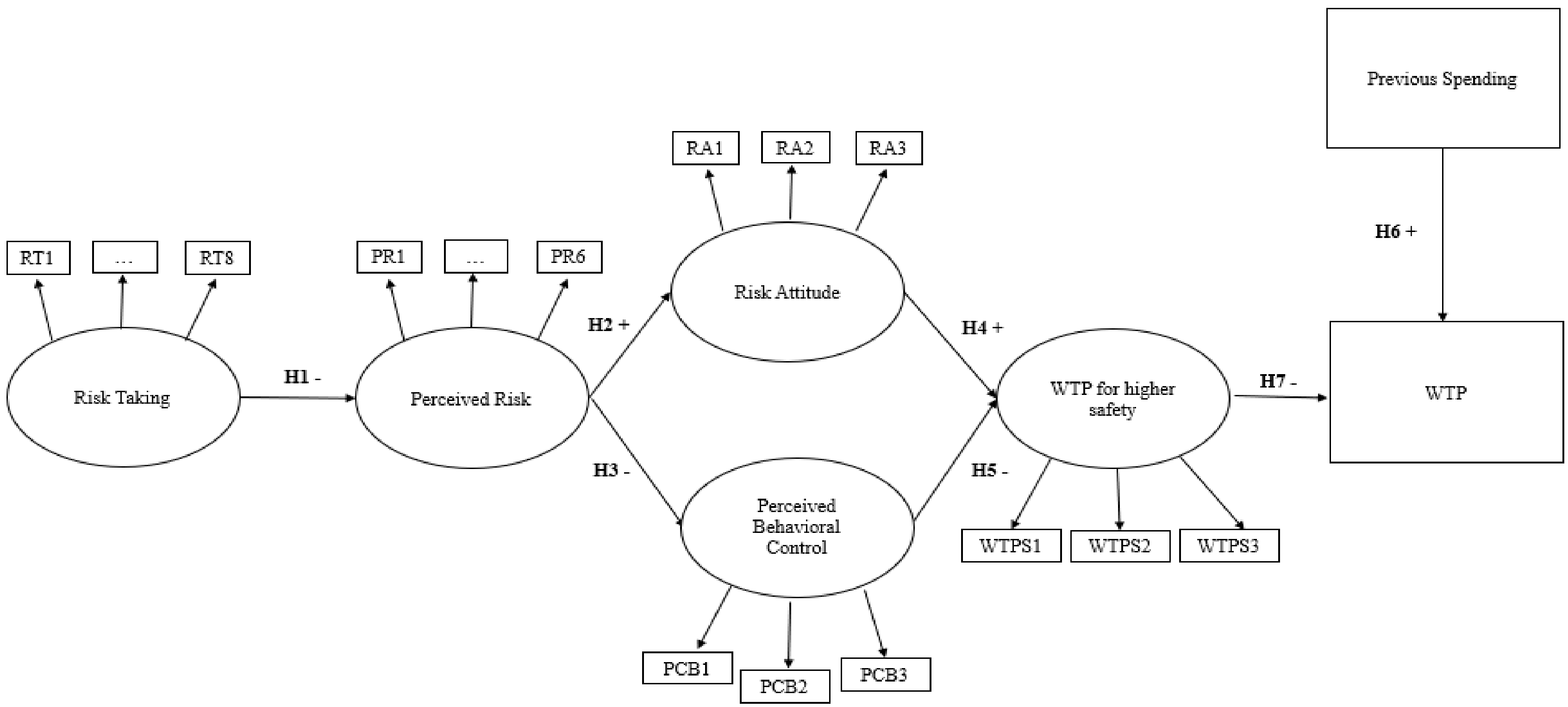
H4 The higher one's risk attitude from COVID-19, the higher their WTP for better safety services.

H5 The higher one's perceived control behavior over sporting event participation, the lower their WTP for better safety services.

H7 The higher one's WTP for better safety services, the lower willingness to pay to attend NFL games during the COVID-19 pandemic.

Figure 4.2

Modified Model for National Football League Fans' Willingness to Pay



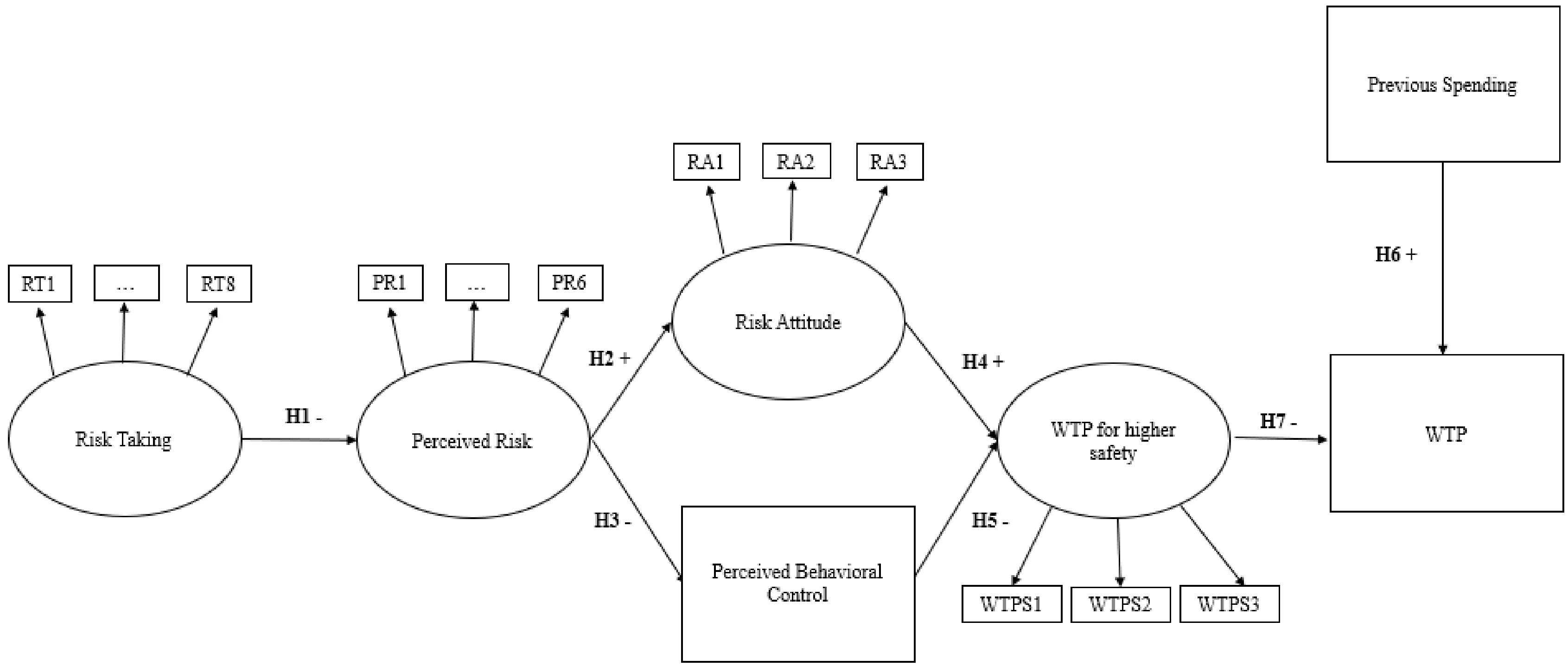
Especially, seven direct paths were investigated (Risk Taking → Perceived Risk; Perceived Risk → Risk Attitude; Perceived Risk → Behavioral Control; Risk Attitude → WTP for Safety; Perceived Behavioral Control → WTP for higher safety; Previous Spending → WTP; WTP for higher safety → WTP).

Although the hypotheses were redefined, the model was still not identified due to possible parameter problems involving one of the items measuring Perceived Behavioral Control (PCB): PCB2 (I am able to participate sporting event during COVID-19). Specifically, the model could not be identified with PCB2 by having standardized estimate of 1 for a path coefficient that could indicate potential model misspecification. In other words, standardized estimate of 1 could occur if there is an error in how the variables are measured, or if the theoretical assumptions of the model are incorrect. Moreover, perfect relationship could be a problem in some cases, such as when the relationship is not theoretically plausible or when there is no room for error or variability in the model.

A possible reason could be the misleading question that creates redundancy. All three questions of PCB ask about participants' abilities and control to participate in a sporting event during COVID-19 without any contents of health risks of COVID-19. In other words, various factors (e.g., income change) could be considered to answer questions of PCB. Additionally, without PCB2, the model was also not identified with a problem involving parameters of PCB. Therefore, a modified model was developed again to measure perceived behavioral control with a single indicator by computing the mean of three questions (see Figure 4.3). Specifically, I computed fixed value for the single indicator variable's error term by multiplying the indicator variable's observed variance by (1 – the estimated reliability for the PCB scale). As a result, the model was identified with acceptable /marginal fit, $\chi 2$ (df) = 886.89 (205), $p < .001$, CFI = .97, TLI = .97, RMSEA = .09, 90% CI [.08, .10], with the exception of the RMSEA which suggested poor fit.

Figure 4.3

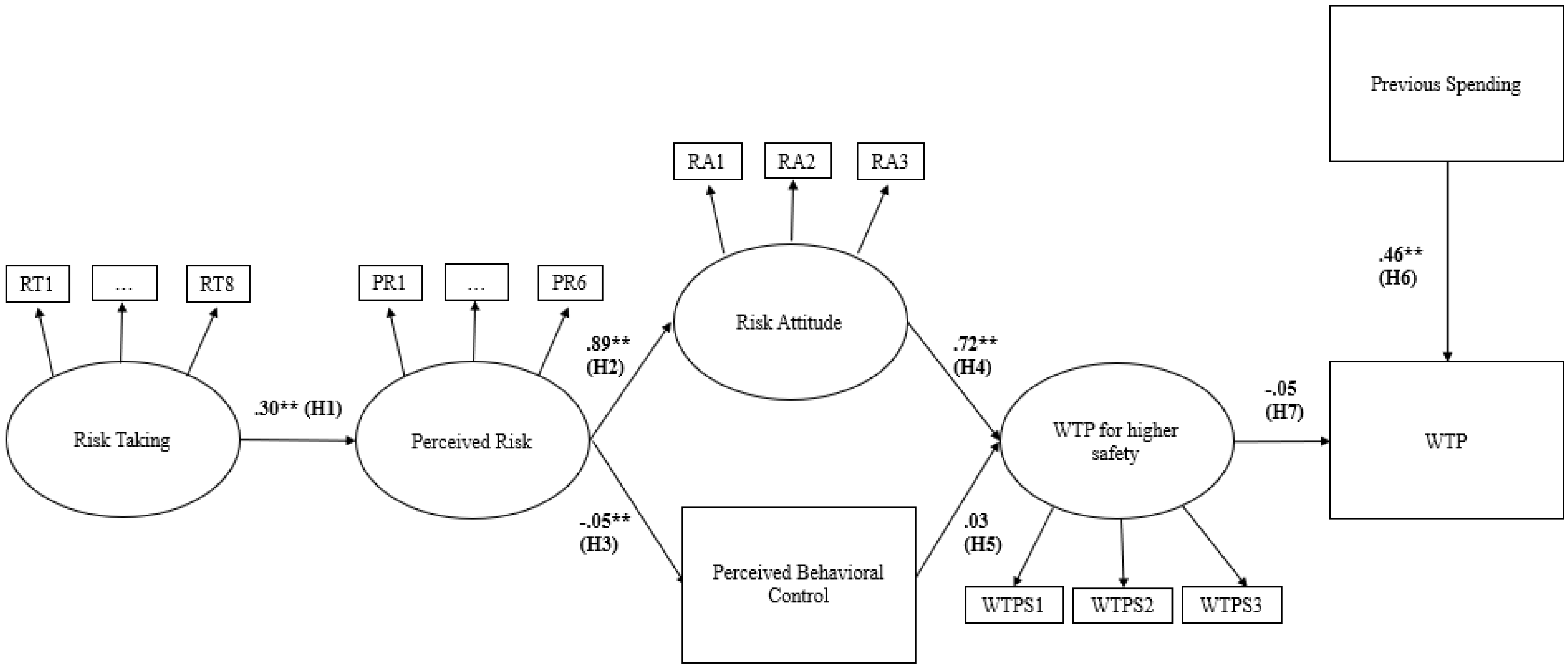
Final Model for National Football League Fans' Willingness to Pay



The study found that although risk taking and perceived risk has a statistically significant, positive relationship (standardized $\beta = .30$, standard error [SE] = .04, $p < .001$), H1, which hypothesized a negative relationship between risk-taking and perceived risk, was not supported by the data. In addition, H2 and H3, which proposed a positive relationship between perceived risk and risk attitude (standardized $\beta = .89$, standard error [SE] = .02, $p < .01$) and a negative relationship between perceived risk and perceived behavioral control (standardized $\beta = -.05$, standard error [SE] = .04, $p < .01$), respectively, were supported. H4 was also supported, indicating a positive relationship between risk attitude and willingness to pay for better safety services (standardized $\beta = .72$, standard error [SE] = .03, $p < .01$). However, H5 was not supported, as there was no statistically significant relationship between perceived behavioral control and willingness to pay for higher safety (standardized $\beta = .03$, standard error [SE] = .03, $p = .41$). The study also revealed that previous spending on NFL tickets was positively associated with willingness to pay during COVID-19 (H6; standardized $\beta = .46$, standard error [SE] = .01, $p < .01$), while there is no significant association between willingness to pay for better safety services and willingness to pay during COVID-19 (H7; standardized $\beta = -.05$, standard error [SE] = .04, $p = .19$) (see Figure 4.4).

Figure 4.4

Findings of Final Structural Equation Model



Note. The path coefficients are standardized.
**p < .05, **p < .01*

Chapter Summary

In the current chapter, the results of the data analysis were reported from multilevel modeling and structural equation modeling (SEM). In the first part of the chapter, descriptive statistics of secondary data observations were reported. Descriptive statistics are important in research as they provide a foundation for further data analysis and interpretation. They help researchers and readers to understand the characteristics of the data they are working with and to make informed decisions about the appropriate statistical tests to use for further analysis. Following examination of the descriptive statistics, two multilevel regression analyses were conducted to identify the relationship between COVID-19 health risks on the secondary market ticket price and the number of attendees. Moreover, the analyses were used to identify variables that significantly explain the NFL's ticket price and attendance demand amid the pandemic era. In the second part of the chapter, a confirmatory factor analysis (CFA) was also conducted, including correlation analysis, reliability estimation, and validity tests. Furthermore, structural equation modeling (SEM) results were presented, indicating significant path relationships supporting five of seven proposed and modified hypotheses. Finally, the next chapter (Chapter V) delves into a comprehensive analysis and discussion of the reported results.

CHAPTER V

DISCUSSION

In this chapter, the study's findings are discussed, along with their implications. Also, as the delimitations and limitations of the study were discussed in Chapter I, opportunities for future research are presented with unanticipated (de)limitations. The purpose of this study was to examine the impact of health risks (COVID-19 cases and deaths) on secondary market ticket prices, number of attendees, and fans' willingness to pay for tickets in the National Football League. Although secondary market ticket price and attendance demand were investigated in multiple studies (e.g., Forrest & Simmons, 2002; Hansen & Gauthier, 1989; Kemper & Breuer, 2015; Shapiro & Drayer, 2014; Shapiro et al., 2021), there is still a lack of understanding of the exceptional circumstances associated with the COVID-19 pandemic.

As discussed with the purpose of this study, understanding the secondary market ticket price and the number of attendees is crucial for various reasons, particularly in the sport industry. One of the primary reasons is the financial impact of these variables. In many cases, the secondary market ticket price and the number of attendees can significantly affect the revenue generated by a sporting event (Dees et al., 2021). By understanding the factors that influence ticket price and attendance demand, sporting event organizers and ticket price decision-makers can make informed decisions about pricing strategies and marketing efforts to optimize revenue. In addition to financial considerations, understanding the secondary market ticket price and the number of attendees can provide valuable insights into market demand (Shapiro & Drayer, 2014). By analyzing these variables, sport organizations can identify trends and patterns in consumer behavior, allowing them to make data-driven decisions about future events. Overall, by considering ticket price and attendance determinants, sport organizations can optimize revenue, create a positive fan experience, gain valuable market insights, and build investor confidence.

With the importance of secondary market ticket prices and attendance demand, understanding a sport fans' willingness to pay is crucial for sport organizations for several reasons. Similar to ticket price and attendance demand, revenue generation is one of the most significant reasons (Kaffashi et al., 2015). By understanding a fans' willingness to pay, sport organizations can set prices for their products and services more effectively (Popp et al., 2018). They can optimize their pricing strategies to maximize revenue without pricing themselves out of the market. In addition to revenue generation, understanding a fans' willingness to pay is also important for marketing strategy (Breidert et al., 2006). By understanding what fans are willing to pay for, sport organizations can create targeted marketing campaigns that are more likely to resonate with their target audience. Moreover, understanding a fans' willingness to pay can help sport teams create a stronger connection with their fan base. By tailoring their offerings to meet the needs and desires of their fans, teams can create a more engaged and loyal following. Understanding the needs and wants of customers can lead to increased revenue and success both on and off the field. The measurement of willingness to pay in sport-related literature was limited to transaction prices (e.g., Popp et al., 2018). As a result, posing open-ended questions about willingness to pay during the pandemic can aid stakeholders in the sport industry in comprehending fans' intentions to attend sporting events at an acceptable price range.

Impact of Coronavirus Disease 2019

As expounded in Chapters I and II, the COVID-19 pandemic wrought unprecedented alterations to the global community's social, economic, educational, and cultural spheres (e.g., Pokhrel & Chhetri, 2021; Singh & Singh, 2020). The impact of COVID-19 on various industries has been scrutinized, including its correlation with secondary market ticket prices and attendance demand in the sport industry, as explored by research questions 1 through 4. While each research question addresses a distinct aspect of the issue, they should be discussed collectively since COVID-19 cases and deaths are pertinent to health risks associated with the pandemic (Sim, 2020). At the same time, secondary market ticket prices and attendance demand are relevant to the behavior of sport industry stakeholders (Shapiro & Drayer, 2014). As reported in Chapter IV, a statistically significant and negative correlation exists between COVID-19 cases and the number of attendees. However, the COVID-19 deaths did not significantly explain NFL attendance demand changes in the current study. Conversely, when the COVID-19 related deaths significantly explained resellers' ticket pricing decision-making, the COVID-19 cases did not have a significant relationship with secondary market ticket pricing.

Although COVID-19 cases and deaths play distinct roles between ticket price and attendance demand, this study found that resellers and fans consider health safety threats in decision-making (i.e., ticket pricing determination and participation in sporting events). One potential explanation for the observed phenomenon could be the profound negative impact of the COVID-19 pandemic on the overall experiences of stakeholders within the sport industry (e.g., Drewes et al., 2021; Mirehie & Cho, 2022). As a result of the significant impact of COVID-19 on the sport industry, it is plausible that resellers and fans would develop an increased level of perceived risk associated with the virus, potentially leading to negative behavioral outcomes, such as a reluctance to purchase tickets or attend live sporting events due to health risks and behavioral restrictions (e.g., Funahashi et al., 2022).

Undeniably, the adverse effects of the global health crisis have had far-reaching consequences on the sector, as a multitude of major international tournaments and leagues were suspended or canceled, leading to significant losses for sport organizations and major disruptions to athletes' schedules and teams alike. As a result of the pandemic, sport organizations have had to alter their operations and activities, such as training, travel, and broadcasting, by adopting new technologies and approaches to maintain their operations, as reported by Skinner and Smith (2021). However, due to insufficient comprehension of consumer demand and behavior in the sport industry, any novel and advanced approaches concerning COVID-19 can hold little significance. Moreover, as experienced with expanding broadcasting, developed technologies could negatively impact resellers and sport teams' gate revenues (e.g., Lee, 2006; Storm et al., 2018; Wallrafen et al., 2022). In other words, as fans have expanded platforms and technologies to engage with sport, fans would not risk attending the sporting event physically, resulting in decreased ticket prices and attendance demand. Additionally, the COVID-19 pandemic has had a significant impact on individual performance that contributes to a level of team performance (i.e., one of the significant findings of price and demand determinants), such as the mental health and well-being of athletes, coaches, and staff involved in the sport industry, resulting in increased stress, anxiety, and uncertainty, as noted by Mehrsafar et al. (2020).

Additionally, the COVID-19 pandemic has significantly negatively impacted overall sport fan experiences that are strongly related to consumer demand and ticket prices (Alam & Abdurraheem, 2023; Nufer & Fischer, 2013). One of the most significant effects has been the restrictions on attendance at sporting events, with many events being held without or with fewer fans. As a result, the atmosphere at sporting events has been impacted, with the absence of fans leading to a noticeable difference in the energy and excitement of the events. The inability to attend games or matches in person has also led to a decline in the social aspect of being a sport fan, with many people missing the sense of community and camaraderie that comes with attending games with friends and fellow supporters (Nicholson et al., 2014). Moreover, the impact of COVID-19 on the economy has resulted in many people being unable to afford to attend sporting events due to financial constraints (Akbulaev et al., 2020). The unpredictability of schedules and event cancellations also created uncertainty and frustration for sport fans who rely on the regularity of sporting events as a form of entertainment and escape. To mitigate the impact of the pandemic on the sport fan experience, some sport organizations have implemented virtual fan experiences and interactive digital platforms to engage with fans and maintain a sense of community. However, it is undeniable that the pandemic has significantly impacted the traditional sport fan experience and the industry, which could affect lower ticket prices and demand with increased risk of COVID-19.

From a broader to detailed perspective, the deleterious effects of COVID-19 on the secondary market ticket prices could be further compounded by resellers' diminished anticipation of robust demand, which may also contribute to the observed phenomenon of lower ticket prices during periods of high COVID-19 deaths. This explanation can be substantiated by examining the correlation between price and demand. When there is a low demand for a product or service, resellers may lower prices to stimulate demand and encourage sales (Hamilton & Price, 2019). When COVID-19 deaths increase in a region, people may become more cautious about attending public events, including sporting games. Specifically, as an illustration, the work of Reade et al.

(2021) indicates that consumer demand in the top European soccer leagues was negatively affected by newly reported COVID-19 deaths.

The related industries (e.g., tourism industry) findings also suggest that secondary market resellers may have lower expectations regarding the demand for sporting event participants in addition to the sport industry. The COVID-19 pandemic has significantly impacted tourist demand, with many countries experiencing a sharp decline in tourist arrivals and revenue (e.g., Haryanto, 2020). There was a significantly lower demand due to several factors, including fears over health and safety (Gössling et al., 2021). In other words, the perceived risk of COVID-19 has been a significant factor in the decline of tourism demand. Travelers may perceive a higher risk of contracting the virus while traveling, which can deter them from making travel plans or result in the cancellation of existing plans. As a result, many tourism businesses have seen a sharp decline in revenue, and some have been forced to close permanently.

These trends lead resellers to expect a decrease in ticket demand, as fans may be less willing to take the risk of being in large crowds. With less ticket demand, resellers may need to lower prices to attract fans and sell out their tickets. Additionally, when there is uncertainty or fear surrounding public health, people may be more inclined to save their money rather than spend it on leisure activities like sporting events (e.g., Coibion et al., 2020; Ryu & Cho, 2022). A decrease in consumer spending can also decrease demand for tickets and subsequently lower prices. In contrast, when COVID-19 deaths are low and public health concerns are minimal, there may be a higher demand for tickets to live sporting events, which can drive up ticket prices due to increased competition among fans for limited seating.

Although resellers consider COVID-19 deaths as a significant determinant of the ticket price, they did not significantly consider COVID-19 cases. There can be potential reasons for this result when there is a limited understanding of perceived risk and risk behavior between COVID-19 deaths and cases. First, resellers may take COVID-19 deaths more significantly than cases because deaths could be a more concrete and tangible measure of the severity of the pandemic. While case numbers can be informative, they would not represent the seriousness of the virus, as some people may be asymptomatic or have mild symptoms and go untested (Kronbichler et al., 2020). Additionally, NFL fans' demographics could be considered for a significant relationship between ticket prices and COVID-19 deaths. According to Jensen and Haskell (2018), although an average NFL fan's age is 37.1 years old, a considerable number of fans are between the age of 41-60. Based on previous studies (e.g., Jordan et al., 2020), older people have a high risk of death from a virus such as COVID-19. Lastly, resellers may be more concerned with the economic impact of the pandemic, and deaths could have a more significant impact on the economy than cases. When someone dies from COVID-19, they are not only losing their life, but they are also losing their ability to contribute to the workforce and the economy, especially as a household member. For these potential reasons, COVID-19 deaths could be a significant factor for resellers in determining ticket prices for NFL games.

On the contrary, a significant relationship was found between COVID-19 cases and the number of attendees, while COVID-19 deaths did not significantly explain attendance demand. Specifically, as indicated in Chapter IV, high COVID-19 cases were associated with low attendance at NFL stadiums (i.e., low demand for games). The low demand for sporting events during increased COVID-19 cases can be attributed to risk attitude. For example, the fear of contracting the virus at the event can deter people from attending, especially those who are considered to be at a higher risk of severe illness (Reade & Singleton, 2021). Specifically, attending sporting events involves close contact with other attendees, increasing the risk of

COVID-19 transmission. Environmental risk of sporting event can be perceived as particularly high when large crowds are expected, such as in professional sport leagues. In addition, the difficulty in maintaining social distancing measures in a sport venue can add to the perceived risk of transmission. Moreover, government guidelines and regulations can influence the perception of risk (Chen et al., 2021). In many cases, government guidelines have recommended limiting large gatherings and social events to prevent the spread of COVID-19. Although sport organizations started to remove various health and safety protocols slowly, fluctuations in the mask policy corresponded to changes in COVID-19 case numbers. Initially, masks were optional for attendees, but the policy was adjusted to mandate mask-wearing when case numbers fluctuated. Overall, the perceived risk of COVID-19 can lead to less demand for sport due to concerns around transmission, fear of contracting the virus, and government regulations limiting the number of attendees at events (Sánchez-Cañizares et al., 2021).

While there was a significant relationship between COVID-19 cases and attendance at NFL games in the current study, COVID-19-related deaths did not significantly explain attendance demand. Especially there could be some factors that contribute to the significant impact of COVID-19 cases on the number of attendances in NFL games, but not COVID-19 deaths. One possible explanation is that, unlike resellers' expectations, people may perceive the risk of death as relatively low compared to the risk of getting infected with COVID-19. In other words, as discussed, many people infected with COVID-19 might only experience mild or no symptoms. At the same time, the risk of death is relatively low, especially for younger and healthier individuals. Furthermore, the development of vaccines and treatment could be reasons for no significant relationship between COVID-19 death and attendance demand. Vaccines are highly effective in preventing COVID-19 deaths. According to data from clinical trials and real-world studies, COVID-19 vaccines have been shown to significantly reduce the risk of severe illness, hospitalization, and death from the virus (Watson et al., 2022). However, although fans could feel fewer threats of COVID-19 deaths, they would be sensitive to COVID-19 cases with concerns for their families and loved ones. Specifically, they would not like to spread the virus after getting COVID-19 by participating in the sporting event. Therefore, COVID-19 deaths might not have as much impact on attendance demand as the number of cases.

Overall, as previous literature indicated different perspectives of suppliers and buyers (Kleinaltenkamp et al., 2022), this study found different focuses between resellers and attendees on COVID-19. Although resellers and buyers have different perspectives on COVID-19 cases and deaths, COVID-19 health risks are still crucial to pricing strategy and attendance demand in NFL games. As the results of this study reported in Chapter IV, a complex set of factors contributed to the relationship between COVID-19 and demand for sporting events, it is also worth noting that the price of sport tickets and the number of attendees are affected by other factors beyond the COVID-19 pandemic, such as home and away teams current winning percentage, division and conference affiliation, and number of available tickets this study considered.

Price and Attendance Determinants

The behavior of secondary market ticket sellers and attendance demand in the NFL concerning COVID-19 cases and deaths differ, despite both having similar attitudes towards the health risks associated with the virus. Following the impact of COVID-19, this study found similar and different relationships that secondary market ticket pricing and attendance demand have with the other determinants (i.e., control variables) considered in this study.

Secondary Market Ticket Price

With COVID-19 deaths, team performance and ticket-related predictors significantly explained ticket changes in the secondary market. First, secondary market ticket sellers consider team performance with COVID-19 death to determine ticket prices. As reported in Chapter IV, higher ticket prices are determined by a greater current winning percentage of home and away teams. Also, lower ticket prices are expected when the away team did not make playoff games in the previous season. As the team and game quality can be determined by the team's current winning percentage and previous record (e.g., Rascher et al., 2007; Shapiro & Drayer, 2014), resellers tend to increase ticket prices with an expectation of greater demand in the market. A team with a high winning percentage typically indicates that they are likely to play at a high level in their upcoming games. High performance can increase the perceived quality of the game in the eyes of fans, as they anticipate a competitive and exciting match (Mutz & Wahnschaffe, 2016). Fans attend games to be entertained and to experience the thrill of watching their favorite teams compete at a high level. A high winning percentage can signal that the team will likely provide that entertainment level.

Additionally, as team performance consists of offensive and defensive statistics and winning percentages, a high-performing team may feature skilled players capable of making impressive plays and contributing to the game's overall quality. For example, NFL teams with high winning percentages may have distinct offensive and defensive players and teamwork. When fans see these players in action, they may feel a sense of excitement and anticipation about the game and may be more likely to attend games featuring high-performing teams (Da Silva & Las Casas, 2017). In summary, fans perceive games as higher quality when the teams involved have a high winning percentage because such teams are expected to perform well and have skilled players that contribute to the game's overall quality as a team. Fans attend games to be entertained and to witness their favorite teams competing at a high level, which is why a high-performing team can provide this level of entertainment. Hence, NFL resellers consider team performance while deciding the ticket prices for each game.

However, no significant relationship was found between ticket prices and the number of Pro Bowl players. There could be several possible reasons for the unexpected result of star players. First, the high performance of an individual player does not necessarily guarantee a high-quality team performance and game (e.g., Mukherjee et al., 2019). For example, although the data showed a significant positive correlation between the number of Pro Bowl players on the home team and the winning percentage, no significant relationship existed between the number of Pro Bowl players on the away team and the winning percentage. The team's overall performance is one of the critical factors explaining ticket prices. Fans may be more interested in the game's overall quality than watching a specific player, resulting in ticket prices being more closely explained by team performance than individual players. Even if a team has a star player, the impact of that player on ticket prices may be limited if the team is performing poorly overall. Another possible reason for the lack of significant relationships could be the uncertainty of the roster during the COVID-19 era. Although COVID-19 vaccine requirements were released for the NFL's 2022 season, resellers may have yet to determine if star players could play due to COVID-19 illness or other injuries. Therefore, when secondary market sellers considered team performance to determine ticket prices, individual performance may not have been a significant factor in this study.

With team performance, ticket availability was found as a significant determinant that explains changes of secondary market ticket prices. Resellers may decrease ticket prices when there is more availability because of the basic principles of supply and demand. When more tickets are available for a particular game, the supply of tickets is higher than the demand for those tickets (Shapiro et al., 2016a). In this case, resellers may decrease prices to attract more buyers and sell their inventory. Another reason resellers may decrease ticket prices when more availability is present is to avoid the risk of unsold inventory. Resellers may face financial losses if they cannot sell their tickets for a game. Therefore, they may decrease ticket prices to sell as many tickets as possible and minimize their risk of financial loss (Lee et al., 2023). Furthermore, resellers may decrease ticket prices when there is more availability to stay competitive in the secondary ticket market. With many resellers offering tickets for the same game, the competition can be fierce, and resellers may need to adjust their prices to stay competitive and attract buyers. Especially as sporting event tickets are considered perishable goods (i.e., the ticket becomes worthless after a game starts; Sweeting, 2012), resellers need to maintain competitiveness to avoid losing their tickets' monetary value. Overall, resellers decrease ticket prices when more availability is present to attract more buyers, avoid the risk of unsold inventory, and stay competitive in the secondary ticket market.

Attendance Demand

When resellers did not significantly consider game-related predictors (e.g., division and conference affiliation), this study revealed that NFL fans consider division and conference affiliation to participate in NFL games during the COVID-19 pandemic. Although secondary market ticket prices are not significantly associated with division and conference affiliation in the current study, previous literature (e.g., Shapiro & Drayer, 2014; Welki & Zlatoper, 1999) indicates ticket price and attendance demand are significantly determined higher for the divisional and intraconference game for the following reasons: divisional rivalry (Lemke et al., 2010) and geographic and civic pride (Welki & Zlatoper, 1999).

Specifically, divisional rivalry games are essential because they feature two teams that are often geographically close and have a long history of playing each other (Welki & Zlatoper, 1999). The games are usually more intense and passionate because the teams compete not just for a win but also for proud rights and to establish dominance within their division. Moreover, sponsors heavily promote and provide specialized broadcasts for rivalry games within divisions, making them more appealing to consumers. As a result, divisional rivalry games gain attention from various groups, including sports fans, the public, and sports media outlets, as Tyler and Cobbs (2017) observed. Madrigal and Chen (2008) suggest that fans exhibit a stronger emotional attachment to rivalry games due to the potential positive or negative feedback from outgroups based on the game's outcome.

Additionally, divisional games can create a sense of unity among fans of a particular team as they rally around their team in the face of a fierce rival. Fans could consider the importance of divisional games with playoff games. In many sport leagues, such as the NFL, MLB, and NHL, the regular season is divided into divisions, with teams playing most of their games against other teams within their division. In other words, divisional games significantly impact the standings and playoff picture more than games against teams outside the division. These games' intense emotions and high stakes can make them more exciting to watch and create lasting memories for fans. Overall, divisional rivalry games could be an important part of many sport leagues and contribute to the regular season's excitement, intensity, and drama.

With the divisional game, previous literature (e.g., Shapiro & Drayer, 2014) emphasized the importance of conference/league affiliation with consumer demand for a game. Specifically, a higher number of attendees were found with intraconference games. One of the primary reasons is the existence of rivalries between teams in the same conference (Havard, 2014). Intraconference games often involve teams with a long-standing history of competing against each other, which can add extra excitement and intensity to the game. Fans may be drawn to these games because they invest personally in the outcome and want to see their favorite team come out on top against a heated rival. In addition to rivalries, teams in the same conference play against each other more often. Therefore, intraconference games can also significantly impact a team's chances of making the playoffs. Teams within the same conference often compete for the same playoff spots, which can add an extra layer of significance to the game. Fans may be more invested in the outcome of these games, as they know that a win or loss can significantly impact their team's playoff chances. These reasons can lead to a more intense and exciting atmosphere in the stadium.

However, contrary to previous findings, the current study's findings indicate that more attendees are expected with the interconference game. As Tainsky (2010) and Lee et al. (2023) stated, the scarcity of interconference games could be a possible reason. In other words, one of the critical reasons why fans may prefer to attend interconference games is the opportunity to see rare match-ups between teams from different conferences. In most professional sports leagues, teams only play against teams from their own conference a majority of games, with only a limited number of games against teams from the other conference. For example, in the NFL, teams play 16 games in the regular season, with 6 of those games against teams from their own division, four games against teams from another division within their conference, four games against teams from a different conference, and two games against teams from the same conference that finished in the same place in their division the previous season.

With the scheduling policy, a team may only play against specific teams from the other conference once every four years. The limited number of games against teams from the other conference creates a level of rarity that can make interconference games particularly exciting for fans (Lee et al., 2023). For example, a fan of an NFL team in the AFC may only have a chance to see their team play against a star player or historic franchise from the NFC once every four years. This rarity can create a sense of anticipation and excitement leading up to the game, as fans know they may not have another chance to see a particular match-up for several years. As recent studies started to find fans' preferences and higher ticket prices of non-divisional and interconference games, further research is needed to explore changes in fans' tastes for better marketing strategies.

With findings of division and conference affiliation, the results indicate away team's previous performance explain the attendance demand in NFL. When resellers consider most of the home and away team's current and previous performances to determine ticket prices, attendance demand significantly relates to the away team's playoff status in the previous season. There could be potential reasons for this finding. First, there could be a reputation effect on opponents eligible to participate in playoff games. The away team's previous season record might strongly affect their reputation and perception among fans (e.g., Czarnitzki & Stadtmann, 2002). Fans may have high expectations for the team based on their performance in the previous season, which could make them more likely to attend games featuring that team, regardless of their current win percentage. Rascher and Solmes (2007) noted that the quality of the previous season is frequently a decisive factor in the decision-making process for purchasing season tickets. In contrast, the home team's current win percentage may have a more immediate effect on fans' perceptions and expectations of the team.

Another reason could be the novelty effect which refers to the phenomenon where people tend to be more interested in or attracted to new or novel elements rather than what they are familiar with (e.g., Coates & Humphreys, 2005). Specifically, compared to the home team, each opponent could be considered a new and novel team because home team fans have more chances to watch the home team’s game. Therefore, fans may be more likely to attend games when the away team performs well because they could be new and exciting. Also, as previously discussed with conference affiliation, fans would be more likely to attend games to see a team that they do not typically get to see play in person. This novelty effect could drive the positive relationship between the away team’s previous season record and the number of attendances.

Moreover, the substantial loyalty of NFL fans could lead to a lack of significant relationship between the home team's previous record and attendance demand. Fans may be more accustomed to seeing the home team play and may need more motivation to attend the game based on their performance alone. Fans who attend home games may already be loyal to the team and attend games regardless of the team's performance (e.g., Neale & Funk, 2006; Wakefield & Sloan, 1995). Although some possible reasons for the finding were discussed, there could be a limitation to understanding why attendance demand only significantly responded to the away team's previous season record with a limited season. Despite having over 200 games with approximately 70,000 data points, they were limited to one season: NFL 2022 season. Therefore, a more accurate analysis could explain specific findings by including more data points from multiple seasons.

Lastly, the results of this study also found a significant relationship between the number of tickets available in the secondary market and attendance demand. Specifically, the number of attendees decreased in response to more listed tickets in the market despite having decreased ticket prices with more available tickets. One of the possible reasons for this finding could be fans' interest in a game. More ticket availability could represent less interest in an event when all other factors, such as the quality of the event, the popularity of the teams or performers, the time of the event, and the cost of the tickets change in each game (e.g., Wann et al., 2004). If a large number of tickets are still available for an event closer to its date, it could indicate that fans are not as interested in attending the event. A lack of interest could be due to various reasons because each game's conditions could differ. For example, the team or player might not perform well or have a solid fan base, resulting in less ticket demand. Alternatively, the event's timing might be better for fans, or the event's location might be inconvenient. Based on the data, COVID-19 cases could be a critical reason for this study. Specifically, the number of available tickets and COVID-19 cases correlate significantly positively. In other words, when COVID-19 cases increase, more tickets are available because attendance demand decreases with a higher risk of COVID-19 cases, as discussed in the part of COVID-19 impacts. While ticket availability can provide some indication of fan interest, it should be considered alongside other factors that influence fan attendance consistently.

National Football League Fans' Willingness to Pay

In light of the importance of COVID-19 as a factor affecting secondary market ticket prices and attendance demand, it is crucial to determine the willingness of National Football Fans to purchase game tickets during the ongoing pandemic. Sport organizations need to understand their fans' willingness to pay in order to make informed decisions about pricing strategies and revenue optimization (Reynisdottir et al., 2008). By knowing the maximum amount that fans are willing to pay for tickets, teams can set prices that maximize revenue while maintaining high attendance demand with reasonable price ranges. Additionally, understanding fans' willingness to pay can help organizations determine the value of other revenue streams, such as sponsorships, merchandise sales, and premium seating options. In the current pandemic, knowing fans' actual willingness to pay for game tickets can help organizations determine how to balance the need for revenue with the need to ensure the safety of fans and players.

Perceived Risk on Risk Taking

Initially, Hypothesis 1 aimed to investigate the association between NFL fans’ risk-taking behavior and the perceived risk of COVID-19. The hypothesis stated that individuals who identify themselves as risk-takers would have a lower perceived risk of contracting COVID-19, indicating a negative relationship between the two variables (Zhang et al., 2019). However, the findings reported in Chapter IV demonstrated a significant positive relationship between the two variables. To put it differently, the outcome of investigation suggested that the perception of risk regarding COVID-19 may not necessarily be higher among individuals who exhibit high-risk behavior. There could be various reasons that might contribute to such a finding.

Firstly, defining the term "high-risk taker" is crucial. If someone engages in risky behaviors such as not wearing a mask, ignoring social distancing guidelines, or attending large gatherings, they may be perceived as high-risk takers in COVID-19 circumstances. Such behavior could be driven by various factors, such as a lack of awareness about the severity of the disease, skepticism about the effectiveness of preventive measures, or a desire to prioritize personal freedom over public health. In this context, a high perceived risk of COVID-19 could be attributed to a heightened awareness of the potential consequences of risky behaviors (e.g., Rolison et al., 2014). If someone engages in high-risk behavior and is aware of the potential consequences, they may also be more aware of the risks and therefore perceive the threat as more severe. Additionally, those generally more risk-tolerant would be more likely to perceive

COVID-19 as a risk due to their willingness to take risks in other areas of their lives. The positive relationship between risk taking and perceived could be found with these characteristics that result in a more significant concern about the potential consequences of the disease and a higher perceived risk of contracting it.

In addition, the structure of the questionnaire used to assess perceived risk could be another plausible explanation. The first three out of the six statements inquired about participants' emotions regarding COVID-19 (such as "I am fearful of COVID-19"), while the remaining three statements focused on concerns regarding their family and loved ones becoming sick from COVID-19 (such as " I am worried that I or people I love will get sick from COVID-19”). The increased concern or worry among high-risk takers for the safety and well-being of their family members concerning COVID-19 could be due to several factors. As discussed, one potential explanation is that high-risk takers may engage in behaviors that increase the likelihood of contracting and transmitting the virus, which could have detrimental consequences for their loved ones. Consequently, for this study’s respondents, they may experience heightened anxiety or worry regarding the safety of their family (Lin et al., 2020).

Moreover, high-risk takers may possess knowledge about the potential hazards of COVID-19 that occurred in various industries (e.g., stock market; Masters, 1989) but disregard that knowledge when engaging in risky behavior. Risk takers would be less apprehensive than low risk-takers about the potential impact on their family members, particularly those more susceptible to the disease. Such factors may contribute to elevated worry or concern among low-risk takers about their family's safety during the COVID-19 pandemic. However, it is essential to note that this correlation between high risk-taking behavior and a high perceived risk of COVID-19 may not be universally applicable.

With findings that are opposite of what tends to be true most likely reflect a measurement problem. One possible explanation is that the high-risk respondents were providing socially desirable (instead of honest) responses on the items, especially on the item related to concern for others. It's difficult to determine if people are being honest or not on a survey but there are lie scales and measures of social desirability that can sometimes help identify respondents who tend not to be honest or who tend to provide socially desirable responses. Another possible approach would be to do a qualitative study and interview both high and low-risk individuals to gain better insights into their motives for either engaging in or not engaging in high-risk COVID-related behaviors. An additional option would be to do a think-aloud protocol to try to determine the extent to which respondents are responding honestly and accurately. Moreover, this study's findings on the relationship between risk taking and perceived risk could indicate possible validity issues on the perceived risk latent variables with relatively weak path coefficient. Therefore, more research is needed to understand the underlying factors contributing to this relationship.

Risk Attitude on Perceived Risk

With the relationship between risk-taking and perceived risk of COVID-19, the relationship between perceived risk and risk attitude was hypothesized: H2. Specifically, when fans have high perceived risk, they are expected to have a high-risk attitude (i.e., unwilling to attend sporting events; Luo & Lam, 2020). For example, tourism research has shown that an individual's perceived risk is essential in their decision to travel and intention to attend sporting events related to risk attitude (Kim et al., 2021). Luo and Lam also found that their perceived risk significantly influenced the tourists' travel intentions.

The result of the current study supports the findings of the tourism industry. If NFL fans have a high perceived risk of contracting COVID-19, they may choose not to attend a game to avoid potential exposure to the virus. As discussed, the primary reason could be that attending a game involves being close to a large number of people, which increases the risk of virus transmission. Moreover, many sport stadiums and arenas have enclosed spaces, which could further increase the risk of transmission. Fans concerned about their health and safety may choose to avoid events where they perceive a high risk of contracting the virus. Additionally, individuals with underlying health conditions or at higher risk of severe illness from COVID-19 may be more cautious and may choose to avoid attending games altogether. Overall, the decision to attend a game is influenced by various factors, including an individual's perceived risk of contracting the virus, personal circumstances, and level of comfort with risk-taking behavior. Moreover, Lewis and Duch (2021) revealed various inconclusive outcomes, indicating the importance of examining perceived COVID-19 risk concerning diverse demographic variables (e.g., age, gender, and season ticket holder status). This approach could assist sport organizations in comprehending their pricing and marketing tactics more effectively.

Perceived Behavioral Control on Perceived Risk

Perceived risk was also anticipated to impact perceived behavioral control. Especially the negative relationship between perceived risk and behavioral control was expected: H3. As reported in Chapter IV, the result shows that the high perceived risk of COVID-19 decreased as the perceived behavioral control of NFL fans increased. Perceived behavioral control is a crucial factor in the theory of planned behavior, a psychological theory that aims to explain human behavior. The factor pertains to an individual's perceived capability to carry out a specific behavior (Conner & Armitage, 1998). Individuals with high perceived behavioral control believe they have the necessary skills, resources, and knowledge to perform the behavior successfully. Conversely, when individuals have low perceived behavioral control, they believe they lack the skills, resources, or knowledge necessary to perform the behavior successfully.

In the context of the COVID-19 pandemic, although stadiums were fully opened to fans in NFL 2022 season games, high perceived risk and low perceived behavioral control can lead to individuals feeling unable to take the necessary precautions to protect themselves from the virus (Ares et al., 2021). For example, a high perceived risk of COVID-19 can lead to low perceived behavioral control because individuals may feel that the situation is beyond their control and may not have the necessary resources or abilities to manage the risk effectively. Suppose someone perceives that attending a live sporting event during the pandemic puts them at a high risk of contracting the virus. In that case, they may feel that they do not have control over the situation, regardless of whether or not safety protocols are in place. Low perceived behavioral control can lead to decreased confidence and control in attending live sporting events, even if they have a strong desire to do so.

Furthermore, high perceived risk can also lead to increased anxiety or fear, further decreasing perceived behavioral control (Alsolais et al., 2021; Yıldırım et al., 2020). Individuals who are highly anxious or fearful may have difficulty making rational decisions. They may be more likely to engage in behaviors inconsistent with their intentions or goals that can result in risky or unsafe behaviors, despite the individual's initial intentions to act safely and responsibly. Overall, the results indicate a significant relationship between perceived risk and perceived behavioral control, highlighting the importance of fans' perceptions of their ability to control their behavior in attending live sporting events during the COVID-19 pandemic. The finding is particularly relevant for data collection during the end of the pandemic era.

Willingness to Pay for Higher Safety and Perceived Behavioral Control on Risk Attitude

Hypotheses 4 and 5 of this study investigated the influence of risk attitude and perceived behavioral control on the extent to which NFL fans were willing to pay for enhanced safety measures in the stadium. As predicted with H4, this study found a significant positive relationship between risk attitude and willingness to pay for higher safety measures in the stadium among NFL fans. In other words, fans who exhibit a higher-risk attitude towards COVID-19 are more likely to be willing to pay additional costs for enhanced safety measures to minimize the spread of the virus in the stadium.

Fans with a high-risk attitude towards COVID-19 are more aware of the potential health risks associated with attending a live sporting event during the pandemic (Alsolais et al., 2021). As a result, similar to previous findings in the tourism industry (e.g., Sánchez-Cañizares et al., 2021), fans would be more willing to pay for additional safety measures in the stadium to possibly reduce their perceived risk of contracting the virus. These fans may feel that investing in additional safety measures, such as improved ventilation or increased sanitization, would increase their sense of control and mitigate the risk of COVID-19 transmission at the event. Furthermore, risk-tolerant fans may be more likely to attend a live sporting event despite the potential health risks. They thus may be willing to pay more for additional safety measures to reduce their perceived risk. These fans may be willing to invest in additional safety measures to justify their decision to attend the event. They feel they are taking responsible precautions to protect themselves and others.

The significant positive relationship between risk attitude and willingness to pay for additional safety measures could be valuable information for sport organizations to consider, notably as businesses implemented COVID-19 surcharges during the pandemic (Belarmino & Repetti, 2022). A COVID-19 surcharge is an additional fee or tax that some businesses add to their prices or bills to offset the costs associated with implementing new health and safety measures during the COVID-19 pandemic. These measures can include increased cleaning and disinfecting, personal protective equipment for staff, and other measures to prevent the spread of the virus. The surcharge is typically a small percentage of the total cost of the product or service and is added to the customer's bill at the time of purchase or payment. Although the surcharge may represent a small proportion of the overall cost, it could have significant implications for individuals already experiencing financial difficulties during the COVID-19 pandemic. Thus, it is essential to conduct ongoing research to examine the responses of sports enthusiasts toward surcharges to prepare for future pandemics.

Despite a significant positive correlation between risk attitude and the willingness to pay for additional safety, the outcome does not provide evidence in favor of H5. Specifically, there is no significant relationship between perceived behavioral control and willingness to pay for higher safety. There could be possible reasons for this lack of significant relationships. First, based on the survey, the mean willingness to pay for higher safety is 4.5 out of 7. In other words, fans may be willing to pay for additional safety measures regardless of how much control they feel they have over attended the game; this could be because fans prioritize their health and safety over their perceived control over attending a game. It may also be because fans may not see their perceived control over attending a game as relevant to their decision to pay for additional safety measures. Instead, they may be more focused on the perceived effectiveness of the safety measures and the potential benefits of having them in place. Lastly, there could be a possible measurement error as perceived behavioral control latent variable was measured with only a single indicator. Therefore, more research is needed to fully understand the relationship between perceived behavioral control and willingness to pay for higher safety measures when attending live sporting events during the COVID-19 pandemic.

Willingness to Pay for Ticket on Past Spending and Willingness to Pay for Higher Safety

The study utilized structural equation modeling to investigate the willingness of NFL fans to pay for tickets by analyzing their past spending on NFL game tickets and their willingness to pay for enhanced safety measures that are possibly affected by the perceived risk and risk attitude of COVID-19. Specifically, the research examined the relationship between the amount of money fans spent on NFL game tickets before the COVID-19 pandemic and their willingness to pay for tickets during the pandemic: Hypothesis 6. As detailed in Chapter IV, the findings revealed a positive correlation between past spending and willingness to pay, thus supporting H6.

One possible explanation could be the level of fan loyalty, which can be gauged by measuring the amount of time and money spent on merchandise and attending games (e.g., Martin, 2013; Wakefield & Sloan, 1995). Therefore, NFL fans who spent more with high loyalty prior to COVID-19 indicate a greater willingness to pay during COVID-19 as well. Also, highly loyal fans may spend more on tickets for several reasons. First, they may feel a strong emotional connection to their team and the league, and attending games may be an essential part of their fan experience (Da Silva & Las Casas, 2017). They may view attending games as supporting their team, connecting with other fans, and feeling a sense of community and belonging (e.g., Margalit, 2008).

Additionally, highly loyal fans may value the overall fan experience highly and would be willing to pay more for premium seats, VIP experiences, or other amenities (e.g., Wakefield &

Sloan, 1995). This could include access to exclusive stadium areas, upgraded food and beverage options, or special merchandise offers. Finally, highly loyal fans may view attending games as entertainment and would be willing to spend more on tickets to enjoy themselves and have fun (e.g., Neale & Funk, 2006). For these fans, attending games may be a way to escape from everyday life, bond with friends and family, and enjoy the excitement of live sports. Mainly, during the 2020 and 2021 NFL seasons, many fans were either unable to attend games or faced safety restrictions that limited their ability to participate. As a result, highly loyal fans who had previously spent more money on tickets may be more likely to spend additional funds to attend games in the future under general conditions.

In contrast to the relationship between previous spending and willingness to pay for the 2022 NFL season, the results do not support Hypothesis 7. Specifically, the study found no significant relationship between willingness to pay for higher safety measures and willingness to pay for tickets. There could be possible reasons for no significant relationship. First, fans may not view safety as a significant factor in their decision to attend games because they perceive the risk of infection as low or believe that existing safety measures are sufficient. Despite the ongoing COVID-19 pandemic, some fans may feel that attending NFL games is relatively safe from other activities they engage in daily, such as going to work, concerts, and theme parks. Moreover, many NFL teams have implemented various safety measures to protect fans and staff, such as requiring masks, COVID-19 testing centers, promoting social distancing, and increasing cleaning protocols. Fans may feel reassured by these measures and not see the need for additional safety measures requiring them to pay more for tickets.

Additionally, the lack of a significant relationship between willingness to pay for higher safety measures and willingness to pay for tickets may also be related to how the study measured willingness to pay. For example, the study may have yet to capture the nuances of fans' attitudes toward safety and the types of safety measures that they would be willing to pay more for. Fans may have different levels of concern about specific safety risks or different ideas about what types of safety measures are most important. For instance, some fans may prioritize mask-wearing and social distancing, while others may emphasize increased cleaning and sanitation protocols. Without a more nuanced understanding of fans' attitudes toward safety and willingness to pay, it may not be easy to draw firm conclusions about the relationship between safety and ticket prices.

Practical Implications

This study's findings have far-reaching implications for the sport management industry. Particularly, this research holds several practical implications for sport marketers, ticket pricing decision markers, and facility managers, particularly those operating within National Football League (NFL) teams.

To examine the behaviors of NFL resellers and fans during the pandemic period, this study examined secondary market ticket prices and the number of attendances in the NFL 2022 season. Although COVID-19 health risk was reduced with the development of the vaccine and treatment system compared to the peak years, this study found that NFL fans are still concerned about the health and safety issues of COVID-19. The finding that fans worry about COVID-19 health risks has significant practical implications for sport organizations and venues. As previous hospitality industry literature argues (e.g., Gursoy & Chi, 2020; Vandenhaute et al., 2022), one of the most critical implications is the consideration of additional safety measures to address fan concerns about the virus.

Higher protection elements may include enhanced cleaning protocols, mandatory mask-wearing, and social distancing measures to help reduce the spread of the virus and alleviate fan concerns. These measures can be costly for sport organizations and venues, but they are crucial for maintaining fan confidence and ensuring the safety of attendees. In addition to safety measures, the stakeholders' concern about COVID-19 health risks may also impact sport organizations' marketing strategies. With fan safety being a top priority, sport organizations may need to adjust their marketing strategies to emphasize safety and cleanliness measures and promote their events' excitement and entertainment value. An additional marketing strategy emphasizing improved safety at sporting events could alleviate fan concerns and encourage attendance. In summary, the finding that fans worry about COVID-19 health risks has significant practical implications for the sport industry. Sport organizations and venues need to prioritize fan and player safety measures in their operations and marketing strategies to maintain fan confidence and ensure the safety of attendees. These measures may be costly, but they are essential for the industry's long-term health.

In light of secondary market ticket pricing and attendance demand, sport organizations could consider implementing a pandemic surcharge to improve stadium safety measures. As discussed earlier, this study revealed that NFL fans are willing to pay extra for higher-quality safety services. There is a positive relationship between risk attitude and willingness to pay for increased safety. During the COVID-19 pandemic, the sport industry faced numerous challenges, including safety concerns and financial difficulties. As a result, many sport organizations were forced to terminate the contracts of several employees due to the lack of games and fans in the stadium, which led to financial constraints.

A pandemic surcharge may be a feasible solution to recover financial losses and ensure safety within stadiums, similar to what the restaurant industry has done. Like the sport industry, the restaurant industry faced safety and financial challenges due to mandatory closures and limited capacity. Consequently, some restaurants added a COVID-19 surcharge to their bills to recoup financial losses. Although some customers may perceive the COVID-19 surcharge as an unfair fee (Callahan & Nguyen, 2020), others believe it is more transparent for consumers than increased menu prices (Wharton, 2020). Furthermore, Belarmino and Repetti (2022) found that customers who observed employees wearing masks had a tremendous increase in willingness to pay (WTP), while customers who noticed employees not wearing masks had the most significant decrease in WTP. Therefore, to implement an additional pandemic-related surcharge, sport organizations should consider what they can do better to increase fans' willingness to pay for additional safety, despite receiving support from fans.

The current study emphasizes the potential implementation of a pandemic surcharge in future pandemic-related situations and the significance of prior spending on fans' willingness to pay for tickets during the pandemic. As discussed earlier, COVID-19 was the first pandemic to halt global sport leagues for an extended period, leaving sport organizations unsure of fans' willingness to pay for event participation. Safety and financial concerns may also deter some fans from returning to the stadium. While the willingness of fans to pay for higher safety may not be a reliable measure of their willingness to pay for NFL ticket prices due to the absence of a significant relationship, the study suggests that their past spending on tickets could serve as a pricing strategy during the pandemic period to determine the acceptable price range for fans. By estimating the acceptable price range for fans based on their previous spending behavior, sport organizations can better target their pricing to attract more fans to attend games while also recouping financial losses from the pandemic. This information can also inform marketing and promotional efforts to encourage fans to return to the stadium and attend sporting events, emphasizing the value of the experience and the safety measures in place.

With COVID-19-related practical implications from secondary market ticket prices, attendance demand, and fans' willingness to pay, NFL teams need to focus on maintaining high-quality games for a more significant number of participants and revenue in the market. In other words, teams may need to invest resources in their rosters and coaching staff to ensure they are competitive and can consistently produce high-quality games. Also, the NFL should consider ways to level the playing field across all teams to ensure that every game is competitive and high-quality consistently. Strategies could involve salary caps and player drafts to promote more even distribution of talent across the league. Finally, the finding may have implications for the league's marketing strategy. By emphasizing the importance of high-quality games, the NFL can attract more casual fans who are primarily interested in the entertainment value of the games. For example, teams and leagues can highlight specific matchups, star players, or other aspects of the game that are likely to be particularly exciting or high scoring, especially when an opponent was eligible for the playoff in a previous season and has a high current win percentage, the opponent's quality can be emphasized.

Lastly, as most sport leagues have done, the NFL should consistently promote their divisional games by highlighting the history of the rivalry between their team and their divisional opponents, as well as the importance of these games in terms of playoff seeding and divisional standings. With these strategies, sport organizations can generate excitement and anticipation among fans leading to these games. Sport teams and marketers also should focus on interconference games. Specifically, previous findings indicate higher ticket prices and attendance demand were found with intraconference games, which marketers and sponsors focus on their advertising. However, with the current study's findings, the importance of interconference should be reviewed with its scarcity. For example, teams and leagues may want to consider scheduling interconference games in prime time slots or on holidays or weekends when more fans may be able to attend or watch on television. As fans' tastes change over time, the impact of divisional and conference/league affiliation should be considered consistently with marketing and revenue generation strategies.

Future Research Directions

This study investigates the impact of COVID-19 on three objectives - ticket prices, attendance, and willingness to pay - that have yet to be explored in the National Football League (NFL). However, further research is necessary to gain a more comprehensive understanding of the effects of COVID-19 on the sport industry.

First, as discussed in the delimitation and limitation section of Chapter I, this study concentrated on the health risk of COVID-19: COVID-19 cases and deaths. However, the COVID-19 pandemic has had far-reaching and multi-faceted impacts on society, including economic, social, educational, and environmental. With diverse types of impacts, future research should include COVID-19 factors that have the potential to change sport fans' attitudes, decision-making process, and willingness to pay to attend a sporting event. Specifically, economic impacts can be considered because of their possible relationship to the fans' purchasing behaviors. One of the most significant economic impacts has been the massive job losses due to the pandemic (Montenovo et al., 2022). Millions of people worldwide have lost their jobs or experienced reduced work hours, particularly in industries that rely on in-person interactions, such as travel, hospitality, and entertainment. Unemployment has caused significant financial stress for many households and has had a ripple effect throughout the economy, as people are less able to spend money on goods and services (Georgarakos & Kenny, 2022).

Concerning COVID-19 and revenue generation in the sport industry, sponsorship and advertising can be considered in future research with their importance as a revenue stream (Dees et al., 2021). Sponsorship and advertising are essential sources of revenue for many sport teams and organizations, and the pandemic has likely had a significant impact on these revenue streams. With many sporting events and leagues being canceled or postponed, there are fewer opportunities for sponsors and advertisers to reach their target audiences through these channels. Additionally, many businesses have reduced their marketing budgets in response to the economic uncertainty caused by the pandemic, further reducing the demand for sponsorship and advertising opportunities (Bara et al., 2021; O'Reilly & Abeza, 2020). Future studies could explore how changes in sponsorship and advertising revenues have impacted the sport industry and how sport organizations have adapted to these changes. For example, some sport teams may have been able to pivot to digital advertising and social media marketing to reach their audiences during the pandemic. Others may have had to find new ways to engage with sponsors and advertisers, such as through virtual events or other online platforms (e.g., Madray, 2020). Understanding the impact of the pandemic on sponsorship and advertising revenues is vital for the sport industry, as it can help organizations to make informed decisions about how to allocate their resources and adapt to the changing landscape. By examining these aspects of the sport industry, future studies can provide a more comprehensive understanding of the impact of the pandemic on this important sector of the economy.

While this research focused on the impact of COVID-19 on the NFL, future research should examine the effects of the pandemic on various sport leagues worldwide. Comparing the impacts of COVID-19 on different sport leagues globally can provide valuable insights into how the pandemic has affected sport organizations, fans, and the industry as a whole. One sport league that would be particularly interesting to compare to the NFL is the National Basketball Association (NBA), which has a more international fan base with a significant presence in China and other parts of Asia (Zhou et al., 2017). Similarly, Major League Baseball (MLB) and European soccer leagues such as the English Premier League, La Liga (Spain league), and the German Bundesliga have unique characteristics that may have been affected differently by the pandemic. For example, the MLB has a longer season than most other sport leagues, which may have made it more challenging to reschedule games in the event of COVID-19 outbreaks. European soccer leagues, on the other hand, have a more global fan base and rely heavily on international travel for matches and events (Owonikoko & Rookwood, 2022). By comparing the impacts of COVID-19 on different sport leagues globally, future studies can provide a more comprehensive understanding of how the pandemic has affected the sport industry. This information can be valuable not only for sport organizations and marketers but also for policymakers and other stakeholders interested in the pandemic's economic and social impacts on different sectors of the economy. However, the cooperation of secondary market platforms becomes essential due to the lack of availability of past ticket price data in open sources.

In conclusion, future research on pricing and attendance in the sport industry should consider the nested structure of data observations by adopting multilevel modeling analysis. Many studies on demand for ticket prices and attendance in sport leagues have a nested structure of data observations, where data collected by teams are nested within the teams themselves. Despite this, there needs to be more research on using multilevel modeling to analyze this type of data, which could result in more accurate and reliable analysis. Therefore, future research needs to consider multilevel modeling as a method of analysis for pricing and attendance in the sport industry. Multilevel modeling analysis can help account for the variability between teams and within teams themselves, leading to more accurate and reliable results.

Moreover, multilevel modeling can help account for unobserved heterogeneity in pricing and attendance demand, which includes factors such as differences in fan behavior and preferences and the impact of external factors such as changes in the economy or other sporting events. By controlling these factors at both the team and individual levels, researchers can better isolate the effects of pricing and attendance on demand. In conclusion, using multilevel modeling analysis in future research on pricing and attendance in the sport industry can provide valuable insights into the factors affecting ticket demand and attendance. By considering the nested structure of data observations and controlling for unobserved heterogeneity, researchers can provide more accurate and reliable analysis to inform decision-making by sport organizations and policymakers. Furthermore, it can shed light on the underlying mechanisms that drive the relationship between pricing and attendance, providing a more comprehensive understanding of the dynamics of the sport industry.

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APPENDIX A

INSTITUTIONAL REVIEW BOARD APPROVAL LETTER

UNIVERSITY OF
NORTHERN COLORADO

Institutional Review Board

Date:	11/11/2022
Principal Investigator:	Yo Han Lee
Committee Action:	**IRB EXEMPT DETERMINATION – New Protocol**
Action Date:	11/11/2022
Protocol Number:	2211046111
Protocol Title:	Impact of COVID-19: Secondary Ticket Market Price, Attendance Demand, and Willingness to Pay in NFL
Expiration Date:	

The University of Northern Colorado Institutional Review Board has reviewed your protocol and determined your project to be exempt under 45 CFR 46.104(d)(702) for research involving

Category 2 (2018): EDUCATIONAL TESTS, SURVEYS, INTERVIEWS, OR OBSERVATIONS OF PUBLIC BEHAVIOR. Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: (i) The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects; (ii) Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or (iii) The information obtained is recorded by the investigator in such a manner that the identity of the human subjects can readily be ascertained, directly or through identifiers linked to the subjects, and an IRB conducts a limited IRB review to make the determination required by 45 CFR 46.111(a)(7).

You may begin conducting your research as outlined in your protocol. Your study does not require further review from the IRB, unless changes need to be made to your approved protocol.

As the Principal Investigator (PI), you are still responsible for contacting the UNC IRB office if and when:

UNIVERSITY OF
NORTHERN COLORADO

Institutional Review Board

- You wish to deviate from the described protocol and would like to formally submit a modification request. Prior IRB approval must be obtained before any changes can be implemented (except to eliminate an immediate hazard to research participants).
- You make changes to the research personnel working on this study (add or drop research staff on this protocol).
- At the end of the study or before you leave The University of Northern Colorado and are no longer a student or employee, to request your protocol be closed. *You cannot continue to reference UNC on any documents (including the informed consent form) or conduct the study under the auspices of UNC if you are no longer a student/employee of this university.
- You have received or have been made aware of any complaints, problems, or adverse events that are related or possibly related to participation in the research.

If you have any questions, please contact the Research Compliance Manager, Nicole Morse, at 970-351-1910 or via e-mail at nicole.morse@unco.edu. Additional information concerning the requirements for the protection of human subjects may be found at the Office of Human Research Protection website - http://hhs.gov/ohrp/ and https://www.unco.edu/research/research-integrity-and-compliance/institutional-review-board/.

Sincerely,

Nicole Morse
Research Compliance Manager

University of Northern Colorado: FWA00000784

APPENDIX B

RSTUIO SYNTAX FOR MULTILEVEL MODELING

MULTILEVEL MODELING ANALYSIS

```
Install.packages("lme4")
Library(lme4)
```

Normal Single Level Model

```
TP_1L <- lm(TP ~ 1, data = RMultilevel)
summary(TP_1L)
```

Unconditional Means Model (Level-1 Model)

```
TP_1LGW <- lmer(TP ~ (1|GW), REML=FALSE, data = RMultilevel)
summary(TP_1LGW)
anova(TP_1LGW, price_1L)
```

Level-2 Model with weather predictors

```
TP_WFH <- lmer(TP ~ WFH + (1|TM), REML=FALSE, data = RMultilevel)
summary(TP_WFH)
performance::r2(MainPrice_WFH)
anova(TP_WFH, price_1LTM)
```

Level-2 Final Model

```
TP_DEATH <- lmer(TP~ WFH + HPO + APO + HWP + AWP + AVA + CASE + DEATH +
(1|TM), REML=FALSE, data = RMultilevel)
summary(TP_DEATH)
performance::r2(TP_DEATH)

anova(TP_DEATH, TP_CASE)
```

APPENDIX C

MPLUS SYNTAX FOR MACDONALD'S OMEGA TESTING

```
TITLE: Omega Testing for Risk Taking
DATA: FILE IS Model1.csv;
VARIABLE:

    NAMES ARE
    RT1 RT2 RT3 RT4 RT5 RT6 RT7 RT8
    PR1 PR2 PR3 PR4 PR5 PR6
    RA1 RA2 RA3
    PCB1 PCB2 PCB3 MPCB
    PWTP
    WTP
    WPSS1 WPSS2 WPSS3;

    USEVARIABLES ARE
    RT1 RT2 RT3 RT4 RT5 RT6 RT7 RT8;

    CATEGORICAL ARE
    all;

MODEL: Risktaking by RT1*(RT1)
     RT2(RT2)
     RT3(RT3)
     RT4(RT4)
     RT5(RT5)
     RT6(RT6)
     RT7(RT7)
     RT8(RT8);

     RT1(e1);RT2(e2);RT3(e3);RT4(e4);RT5(e5);RT6(e6);RT7(e7);RT8(e8);

MODEL CONSTRAINT:
     new sumload2 sumevar omega;
     sumload2=(RT1+RT2+RT3+RT4+RT5+RT6+RT7+RT8)**2;
     sumevar=e1+e2+e3+e4+e5+e6+e7+e8;
     omega=sumload2/(sumload2+sumevar);

ANALYSIS: ESTIMATOR=WLSMV;
       Parameterization=theta;
```