2023

Understanding U.S. Customers' Intention to Adopt Robo-Advisor Technology

Deborah Wall
Walden University

Walden University

College of Management and Human Potential

This is to certify that the doctoral dissertation by

Deborah J. Wall

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Daphne Halkias, Committee Chairperson, Management Faculty
Dr. Mohammad Sharifzadeh, Committee Member, Management Faculty
Dr. Kenneth Levitt, University Reviewer, Management Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2023

Abstract

Understanding U. S. Customers' Intention to Adopt Robo-Advisor Technology

by

Deborah J. Wall

MBA, LaSalle University 1988

BS, University of Dayton, 1985

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

Winter 2023

Abstract

Finance and information technology scholars wrote that there is a literature gap on what factors drive investors in Western financial markets to use a Robo-advisor to manage their investments. The purpose of this qualitative, single case study with embedded units is to understand the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor. A single case study design addressed the literature gap, and qualitative data from seven semistructured interviews, reflective field notes, and archival data were triangulated to answer the research question. This study was grounded in a theoretical framework that includes the theory of planned behavior, the technology acceptance model, the unified theory of acceptance, and the use of technology. Thematic analysis revealed nine themes of the study: a) awareness of Robo-advisory systems, (b) perceptions of risk connected to customer's financial literacy, (c) data security risk lowers acceptance of Robo-advisor technology, (d) Robo-advisor is filtering out emotional customer biases, (e) customer ambivalence on Robo-advisor capabilities, (f) perceived ease of use, (g) trust in the Robo-advisor, (h) customer ambivalence on adoption intention, and (i) low adoption intention for customers with low financial literacy. This study's results indicated that financial institutions must still earn customers' trust by protecting their data through secure platforms and processes and customizing Robo advisor services, products, and offers, to their needs. By further understanding retail investors' adoption intentions in using a Robo-advisor, this study's results may drive positive social change by offering pathways to very low-cost, automated financial management advice to a broader segment of new and intermediate investors.

Understanding U. S. Customers' Intention to Adopt Robo-Advisor Technology

by

Deborah J. Wall

MBA, LaSalle University

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

Winter 2023

Dedication

This is dedicated to my beloved, recently departed parents, Kevin and Valerie Wall, who supported and believed in me and told me that I could do anything.

Acknowledgments

Thank you to Dr. Daphne Halkias, who has been my unwavering and wonderful coach and guide, thank you so much for your priceless wisdom and kindness. Your mentorship made this possible. Thanks to Dr. Mohammed Sharifzadeh as well for your help and quiet but constant support.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

Although research has found that the financial services industry has taken an overall cautious approach to adopting artificial intelligence (AI), evidence suggests that banks have launched large investments in developing AI value-driven competencies (Atwal & Bryson, 2021; Jaiwant, 2022). Robo-advisors can be broadly defined as digital advisory services using algorithms to gather information on a customer through an online survey and then automatically invest in the customer based on that data (Bhatia et al., 2021). With the ongoing digital revolution and the growth of these advisors, Robo-advisors are overshadowing traditional advisors in the eyes of retail investment investors (Fisch et al., 2019). To date, limited research to date has investigated Robo-advisor adoption behavior (Fan & Chatterjee, 2020; Tsai & Chen, 2022).

Traditional financial advisors face challenges brought about by the increasing presence of Robo-advisor- based services (Fisch et al., 2019). Successful traditional client-facing financial advisors develop deep relationships with clients over time, invest more time in providing services, and utilize quality administrative and executive support to manage and operate their advisory firms (Fan & Chatterjee, 2020). For retail investors, the Robo-advisor has gained considerable attention in financial decision-making and has emerged as an effective alternative to traditional financial advisors with benefits including lower charged fees, ease of use, and diversified services (Bhatia et al., 2020; Brenner & Meyll, 2020).

Finance and technology scholars remain uncertain about how far the Robo-advisor trend will continue due to early customer adoption barriers and challenges

(Bhattia et al., 2021). Most research studies on the Robo-advisors phenomenon were published in Germany, and only one qualitative study by Atwal and Bryson (2021) on the adoption intention of Robo-advisors by German retail investors. Atwal and Bryson recommended that future replication studies of their qualitative research be conducted in other Western markets to validate their preliminary findings. By further understanding retail investors' adoption intentions in using a Robo-advisor, this study's results may drive positive social change by offering pathways to very low-cost, automated financial management advice to a broader segment of new and intermediate investors.

This introductory chapter will illustrate the background literature leading to the problem statement development and explain the gap in the scholarly literature. Chapter 1 presents the alignment between the problem, purpose, research questions, research design, and conceptual framework. Lastly, this chapter includes the study's significance, assumptions, limitations, and definitions of key terms used throughout this document.

Background of the Study

Finance and technology scholars have raised questions about the emerging popularity of Robo-advisors and traditional human financial advisors (Tsai & Chen, 2022). Robo-advisors have become increasingly popular and have continued to increase since 2008 (Atwal & Bryson, 2021). Robo-advisors popularity has risen from the growing dissatisfaction of the American retail investor with customer service delivery within the financial services sector (DALBAR, 2020). The American Customer Satisfaction Index (2021) is the only national cross-industry measure of customer satisfaction in the United States. It has been measured nationally since 1994 through a random and representative sample questionnaire and is predictive of economic growth and innovation progress. It is used to predict GDP growth. Customer satisfaction measurement for over 25 years across industries shows that financial services satisfaction has hovered slightly over the overall average of 74, at 76. Service-intensive industries have consistently and significantly underperformed consumer goods, manufactured goods, and hospitality. In the American Customer Satisfaction Index (2021), breweries rank higher in satisfaction than financial advisors.

Boratyska (2019) developed a fintech value creation framework including the concepts of digital, innovation, pricing, learning, openness, modernity, and agility and described Fintech as a disruptive technology application for the retail and small business levels, including digital reporting, digital loan origination, payment transfers, and demonetization. The application and availability of these new fintech capabilities appear to be driven by the same unmet customer needs that launched the age of Fintech in financial services (Breidbach et al., 2020). In a generational study, Dagar et al. (2020) sought to understand the importance of Fintech to Millennials and Gen Z by understanding the value Fintech can bring to address unmet customer needs and found a greater appreciation held by Millenials over Gen Z for Fintech. Further recommendations were made in this Millennial study for banks to digitize their financial services to meet the customers' needs, considering that 90% of respondents see that unmet customer needs are a key issue in adopting Fintech services (Dagar et al., 2020).

DALBAR, an investment research firm, reported in 2020 that 82% of investors it surveyed were satisfied with their Robo-advisor during the market crisis brought on by the pandemic n 2020, compared with 71% of investors using an advisor.

DALBAR's (2021) survey included nearly 500 investors in North America working with a Robo-advisor and 500 investors working with a human financial advisor.

The study found that although human advisors were more diligent in communicating with clients than Robo-advisors during the market crisis, less communication by Robo-advisors failed to diminish the trust and confidence of their investors. Investors indicated they were inclined to retain their Robo-advisor following their investment experience during the COVID-19 crisis: 92% vs. 82% of those with human advisors. Customers who showed a favorable attitude toward Robo-advisors believed that the most important advantage stems from the ease of use in initiating the investment process with Robo-advisory platforms, easy accessibility, cost-efficiency, technology, and tax efficiency (Atwal & Bryson, 2021). Limited research has investigated Robo-advisor adoption behavior and whether early adopters will remain their Robo-advisors long-term (Piehlmaier 2022).

Problem Statement

Recently, one of the most significant AI investments in the finance industry has been in the Robo-advisor, an AI-driven virtual financial advisor that provides investors with access to low-cost products and high-quality financial advice (Wexler & Oberland, 2020). The global Robo-advisor market was valued at $4.51 billion in 2019 and is projected to reach $41.07 billion by 2027, growing at a compound annual growth rate of

31.8% from 2020 to 2027 (Statistica, 2021). Traditional financial advisors help the customer by assessing their needs and objectives, defining their level of risk, and investing their customers' money according to this risk (Scholz, 2021). For retail investors, the Robo-advisor has gained considerable attention and has become a growing trend to outnumber traditional financial advisors with benefits due to lower charged fees, ease of use, and diversified services (Bhatia et al., 2020; Brenner & Meyll, 2020). The social problem is that while using Robo-advisors in financial institutions has become a popular trend, early adopters' socio-psychological barriers may thwart the long-term success of this AI application to long-term use (Merkle, 2020; Tsai & Chen, 2022).

While banks are set to invest heavily in developing AI value-driven competencies, the successful adoption of Robo-advisors within the financial services industry will depend on gaining a critical understanding of the customer's potential barriers to AI adoption (Atwal & Bryson, 2021; Tsai & Chen, 2022). In customer-focused front-office applications, the bank customer will play a crucial role in the adoption intention of Robo-advisors (Greve & Meyer, 2021). Finance and information technology scholars wrote that there is a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). The specific management problem is that little is known about the adoption intentions of retail investors across Western financial markets to use a Robo-advisor instead of a human advisor (Hentzen et al.,2022; Piehlmaier, 2022).

Purpose of the Study

The purpose of this qualitative, single case study with embedded units is to understand the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor. This exploratory case study's purpose may address the literature gap on understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (see Piehlmaier, 2022; Zhang et al., 2021). Following Atwal and Bryson’s (2021) recommendation, future replication studies of their qualitative research in other Western markets to validate their preliminary findings on the adoption intention of Robo-advisors in Germany, I used a single case study with an embedded unit design to address this gap within the qualitative paradigm (Yin, 2017). I conducted seven semistructured online interviews with retail investors in US market**s,** meeting the study’s inclusion criteria. Multiple data sources were collected, including reflective journal notes and archival data from media sites on the adoption and use by customers of Robo-advisors within the US financial services industry (see Stake, 2010).

Research Question

How do retail investors in US markets describe their adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor?

Conceptual Framework

The theory of planned behavior (TPB) by Ajzen (1991), the technology acceptance model (TAM; Davis, 1985), and the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) can provide a framework of theories and conceptual models by which to explain customer behavior in financial technology-based platforms and to gain a deep understanding on customer decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022). Research studies on the diffusion of financial technology and Robo-advisors to customers are predominantly grounded on these three adoption models (Atwal & Bryson, 2021).

The TPB was developed by Ajzen (1991) as a prediction tool for intention to behave in a specific manner, assessing attitudes toward the behavior, subjective norms, and perceptions of being in control. In TPB, individual social aims are planned by disposition, abstract standards, and conduct control. TPB has been used to explain and predict behavior across various behavioral domains, including technology adoption (Ajzen, 2020). An extension of TPB was developed by Davis (1985) and named the TAM. Davis et al. (1989) wrote that TAM could explain that users' intention to use an information system is determined by perceived use, usefulness, and attitude toward use. Davis adopted the theoretical views of Ajzen and Fishbein’s (1975) theory of reasoned action (TRA) to show the perceived usefulness and ease of use.

Finally, the UTAUT was proposed by Venkatesh et al. (2003), which replaced the attitude construct in TPB and iterations of TAM and developed their theory using new constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions as critical predictors in the adoption of technology. Research investigating investors’ adoption of Robo-advisory services remains limited, perhaps because of its recent market introduction (Tsai & Chen, 2022). Further elaboration on the logical connections among critical elements of the framework to the study's purpose and its relation to the study approach, research questions, and research method is further explained in Chapter 2.

Nature of the Study

This study's nature is qualitative, aligns with the study's purpose, and provides data for the research question. This study's nature is grounded in the constructivist paradigm to understand how individuals find meaning from social interactions and experiences (Denzin & Lincoln, 2011). Quantitative methods are inappropriate for this study because quantitative research designs examine relationships, test theories, standardize reporting, and collect quantifiable data and a mixed-methods approach is not appropriate because quantitative data is not suitable to answer my research question (Harkiolakis, 2017). The research problem and the study's nature required using a qualitative methodology to explore a complex social process (Merriam & Grenier, 2019). Qualitative research effectively explored the contextual influences on the research issues and addressed why social issues needed further clarification or how questions described processes or behavior (Tracy, 2019).

Qualitative researchers aim to explore people's experiences within a specific context (Tracy, 2019). Constructivists questioned how people perceived the world and interpreted the interactions between individuals and the environment (Cooper & White, 2012). Qualitative research also presented opportunities to evaluate business decisions and explore the reasons behind various aspects of behavior within organizations. A long tradition exists of using case studies in business teachings to generate detailed and holistic knowledge using multiple sources in an information-rich context (Eriksson & Kovalainen, 2015; Yin, 2017).

Researchers used purposeful sampling to identify and select information-rich cases related to the phenomenon of interest (Halkias & Neubert, (2020). Although various purposeful sampling strategies exist, criterion and network sampling should be used in the most common implementation research (Baxter & Jack, 2008). Participants for this case study were recruited using purposeful sampling strategies and screened with the following inclusion criteria: a) adults over the age of 18 residing in the United States; b) 1 year of experience using a Robo-advisor for retail investing; and c) possess knowledge and experience using a traditional financial advisor for investing their money.

I conducted 10 semistructured online interviews with retail investors in US markets meeting the study's inclusion criteria. Schram (2006) recommended that researchers recruit between five to 10 participants for a qualitative study because a larger sample size can lead to weaker research results and compromise in producing detailed, thick descriptions of the phenomena under study. The interview transcripts were analyzed with thematic analysis using Yin's (2017) pattern-matching logic sequence to identify themes. Triangulation of multiple data sources strengthened the study results' trustworthiness on the phenomena under study (Halkias & Neubert, 2020; Tracy, 2019).

Definitions

Adoption intentions: This term refers to the planned use or non-use of Robo-advisors by retail investors (Atwal & Bryson, 2021).

Customer-focused front-office applications: This term refers to digital banking services that allow retail investors to manage deposits, withdrawals, and transfers, direct and authorize investments or purchases, and manage assets and funds (Atwal and Bryson, 2021).

Financial technology-based platforms: This term refers to any digital application or website that is a place where customers can interact and practice decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022).

Retail investment: This term refers to the number of assets that are invested by retail investors (Atwal and Bryson, 2021).

Retail investors: This term refers to consumers who invest their assets/money directly through a retail bank or wealth management investment company through a financial advisor or directly to a digital interface (Atwal and Bryson, 2021).

Robo-advisor: This term refers to an AI-driven virtual financial advisor that provides investors with access to low-cost products and high-quality financial advice (Wexler & Oberland, 2020).

Assumptions

Researchers held onto assumptions presumed to be true when extending a theory for a specific purpose (Halkias & Neubert, 2020). The first assumption was that the sample participants were active customers of financial institutions who have had sufficient interaction with a traditional human-based advisor/agent delivery and Robo-advisors across a spectrum of banking, wealth management, and insurance services. The second assumption was that the Robo-technology delivery has worked as expected. The study participants had not had major technical issues with the Robo-advisor or their technology that would significantly negatively bias their overall view of Robo-advisors (see Yin, 2017).

The third assumption was that I would recruit customers of financial institutions that can accurately compare the experience between human-based and digitally-based money and insurance services across the customer life cycle**.** The fourth that had to be met was that the study participants had had a recent set of both human and digital-based interactions since the value delivery technology changes rapidly and new ways and types of services are being delivered weekly (see Bloomberg & Volpe, 2018).

The fifth assumption was that the sample of qualified respondents would be diverse enough in terms of experience and demographics to provide richness and depth of insights and experiences. The sixth assumption was that the study participants would be honest and forthright about adopting Robo-advisory services, even if it involved the participants admitting their lack of ability to understand how the technology works or how to fully use it (see Merriam & Tisdell, 2015).

Scope and Delimitations

This study captured insights that described adoption intentions by comparing traditional financial services to AI-based Robo-advisors across financial services. Participants for this case study were recruited using a broad pool of financial services customers who would have been given a chance to elect a Robo-advisory digital application or platform. The scope included Robo-advisory services from retail banking, wealth management/financial planning, and insurance services within the United States. Participants for this case study were recruited using purposeful sampling strategies and screened with the following inclusion criteria: a) adults over the age of 18 residing in the United States; b) 1 year of experience using a Robo-advisor for retail investing; and c) possess knowledge and experience using a traditional financial advisor for investing their money.

Rigorous case study designs controlled theoretical variation outside the study's scope to establish transferability (Stake, 2010). The study addressed the research problem within the scope delineated by the purpose of the study and by general observations about intentions and experiences gained from historical interactions with retail human-centered and AI-driven Robo-advisors across age, gender, race, and wealth segment diversity. While banks were set to invest heavily in developing AI value-driven competencies, the successful adoption of Robo-advisors within the financial services industry will depend on gaining a critical understanding of the customer's potential barriers to AI adoption (Tsai & Chen, 2022).

Limitations

Limitations were influences the researcher could not control, shortcomings in the design, study conditions, or restrictions on their methodology affecting results and conclusions (Tracy, 2019). When conducting research, scholars must be well-versed in the limitations of the selected study design, data collection, and analysis methodology to ensure valid and reliable results. The researcher's method and personal bias related to the circumstances and the environment were inherent limitations of qualitative research. This study faced limitations in capturing the up-to-the-minute adoption intentions for the fast-moving space of evolving Robo-advisors across the wide-ranging financial services industry. Specific factors within the study design may also pose limitations (Merriam & Grenier, 2019).

Study participants were purposefully selected; snowball sampling was utilized if the sample size was not initially attained (see Yin, 2017). It was recognized that a small sample size might not represent the larger population of Robo-advisors usage intention challenges. This limitation was mitigated by providing a detailed audit trail and triangulation of interview responses, historical literature, and field notes to collect accurate data to answer the research question (Halkias & Neubert, 2020).

Purposeful and snowball sampling was used to achieve the minimum number of appropriate participants preferred by scholars to provide an information-rich body of in-depth material pertinent to the study (Eriksson & Kovalainen, 2015). When evaluating qualitative research with small sample sizes, distinct environments, and unique experiences, the findings and conclusions may not directly apply to other studies and populations. A study's limitations are characterized by factors in the design or methodology that impact or misinterpret the research results. The researcher's method and personal bias related to the circumstances and the environment were inherent limitations of qualitative research. In this study, specific factors may have also posed limitations. When evaluating qualitative research with small sample sizes, distinct environments, and unique experiences, the findings and conclusions may not have directly applied to other studies and populations (Stake, 2010).

Significance of the Study

Significance to Practice

Assets managed by Robo-advisors reached $1.4 trillion in 2020, with a 47% increase from 2019, and are forecasted to reach $2.5 trillion in 2023. In 2020, 70.5 million investors were using Robo-advisory services, which is expected to increase to 147 million by 2023 (Atwal & Bryson, 2021). While banks are set to invest heavily in developing AI value-driven competencies, the successful adoption of Robo-advisors within the banking industry will depend on gaining a critical understanding of the customer's potential barriers to AI adoption (Tsai & Chen, 2022). Robo-advisory is at a nascent stage and is still emerging and evolving. Therefore, additional information is needed to equip investors better to understand its full capability of handling different financial technology issues (Bhattia et al., 2021). Abraham et al. (2019) suggest it is interesting for researchers to explore whether different Robo-advisors must be designed to cater to different domestic segments of different countries, an area presently under-researched. My study is significant to professional practice to inform marketers when developing strategies to foster awareness and the intention to use and adopt Robo-advisors by retail investors within the United States.

Significance to Theory

Finance and information technology scholars identified a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). Many studies on Robo-advisor adoption have been conducted in Asia; thus, more studies are needed to explore precursors of Robo-advisor adoption within Western financial market contexts to recommend future quantitative studies that will provide some generalizable findings (Atwal & Bryson, 2020; Gan et al. (2021). Research studies on the diffusion of financial technology and Robo-advisors to customers were predominantly grounded in three adoption models: the TPB by Ajzen (1991), the TAM (Davis, 1985), and the UTAUT (Venkatesh et al., 2003) (Atwal & Bryson, 2021). This study was significant to theory because it contributed original, qualitative data to the management and finance body of literature by extending the three adoption models explaining the diffusion of financial technology and Robo-advisors to customers for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022).

Significance to Social Change

The economic recovery from the recent financial crisis paved the way for financial technology (Fintech) and digitalization to make financial services and products more cost-efficient and accessible for retail investors, including the unbanked (Birkenmaier & Fu, 2016). The competition resulting from the emergence of Robo-advisors catalyzed many traditional financial services firms to consider revising their fee structures or integrating Robo-advisory platforms into their offerings to remain competitive in the market.

Robo-advisors offer traditional investment management services at much lower fees than traditional financial advisors and are easy to use and secure(Brenner & Meyll, 2020). Doing good for the community, outperforming benchmarks, and transparency around performance have built greater trust for Robo-investors, while superior customer service is a stronger driver of trust among traditional investors (LendEDU,2021). Nevertheless, finance and technology scholars remain uncertain about how far the Robo-advisor trend will continue due to early customer adoption barriers and challenges (Bhattia et al., 2021). By further understanding retail investors' adoption intentions in using a Robo-advisor, this study's results may drive positive social change by offering pathways to very low-cost, automated financial management advice to a broader segment of new and intermediate investors.

Summary and Transition

While using Robo-advisors in financial institutions has become a popular trend, early adopters' socio-psychological barriers may have thwarted the long-term success of this AI application for long-term use (Merkle, 2020; Tsai & Chen, 2022). While banks are set to invest heavily in developing AI value-driven competencies, the successful adoption of Robo-advisors within the financial services industry will depend on gaining a critical understanding of the customer's potential barriers to AI adoption (Atwal & Bryson, 2021; Tsai & Chen, 2022). The specific management problem was that little is known about the adoption intentions of retail investors across Western financial markets to use a Robo-advisor instead of a human advisor (Hentzen et al.,2022; Piehlmaier, 2022).

The purpose of this qualitative single case study with embedded units was to understand the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor. The TPB by Ajzen (1991), the TAM (Davis, 1985), and the UTAUT (Venkatesh et al., 2003) provided a framework of theories and conceptual models by which to explain customer behavior in financial technology-based platforms and to gain a deep understanding on customer decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022). A qualitative, single case study with embedded units allowed the researcher an in-depth exploration of a **bounded** system (Yin, 2017). The study's data was collected from a semistructured interview, reflective field notes, archival data, peer-reviewed scholarly papers, and triangulation to ensure the trustworthiness of the findings. Robo-advisory is nascent, and additional information was needed to understand its capability better to handle different financial technology issues (Bhattia et al., 2021).

Chapter 2 of this study focuses on developing an appropriate literature search strategy for the study. I provide an expanded view of the current literature, the theories, and the conceptual framework and further supported the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor

Chapter 2: Review of the Literature

The specific management problem is that little is known about the adoption intentions of retail investors across Western financial markets to use a Robo-advisor instead of a human advisor (Hentzen et al., 2022; Piehlmaier, 2022). Robo-advisors can be broadly defined as digital advisory services using algorithms to gather information on a customer through an online survey and then automatically invest in the customer based on that data (Bhatia et al., 2021). With the ongoing digital revolution and the growth of these advisors, Robo-advisors are overshadowing traditional advisors in the eyes of retail investment investors (Fisch et al., 2019). To date, limited research has investigated Robo-advisor adoption behavior (Fan & Chatterjee, 2020; Tsai & Chen, 2022).

The purpose of this qualitative single case study with embedded units was to understand the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor**.** This exploratory case study addressed the literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (see Piehlmaier, 2022; Zhang et al., 2021). There was a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021).

Chapter 2 presents the literature search strategy and the conceptual framework that guides this empirical study. The literature review of this chapter presents a synthesis of knowledge and critical analysis of peer-reviewed scholarly papers on the following topics*: The Theory of Planned Behavior (TPB), the Technology Acceptance Model*

(TAM), the Unified Theory of Acceptance and Use of Technology, The Financial Industry and Robo-Advisors: An Overview, Research Contrasting Traditional Financial Advisors and Robo-Advisors, Creating Customer Value through AI interactions in Financial Services, Factors Driving Investors in Western Financial Markets to use Robo-advisors, Customer Value Delivery at Financial Institutions, and *Intention to Adopt Robo-advisor Services by Consumers in Personal Investing.*

Literature Search Strategy

A literature review search is unique, as it enables a systemic search and analysis spanning diverse research methodologies to combine qualitative and quantitative studies to thoroughly comprehend a phenomenon under review (Tracy, 2019). Inherently related to a literature review's objectives, exploring databases to search for peer-reviewed scholarly papers must be comprehensive, wide-ranging, and varied. The search included manual and electronic databases, reviewing papers referenced in relevant studies, and recommendations from specialist researchers. The criteria, keywords, and phrases used in the search were identified according to the guiding research question (Torraco, 2016). Given the cutting-edge nature of this technology-focused study, the search strategy focused on a mix of classic financial services behavioral research and the latest fintech adoption studies, which have just begun to emerge, especially with the COVID-19 pandemic as an accelerator.

Numerous search engines and databases were used to retrieve exclusive literature from authorities in the field of study. Extraction was made using Google Search. The databases I used to conduct the literature review include the Walden University Library and Google Scholar. Literary searches were conducted through the collections of Emerald Insight, ABI/INFORM, ACM, Business Source Complete, IEEE Xplore, Science Direct, and Sage Premier. The literature review was focused on studies published within the past 5 years to emphasize current research findings.

The literature review was conducted using search terms involving multiple combinations of the following keywords or phrases: *customer engagement and financial service*, *customer experience and financial services*, *customer experience research gaps/and financial services, customer value creation and Robo-advisor financial services, customer value delivery, customer value delivery, and Robo-advisor financial service, fintech adoption, and research gaps,* and *Robo-advisor adoption intentions*. A significant number of peer-reviewed papers reviewed in this literature review were published between 2019 and 2022; except for seminal works, 10% or less of the articles used were published before 2018.

Literature Review Grounding the Conceptual Framework

The TPB by Ajzen (1991), the Technology Acceptance Model (TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) provided a framework of theories and conceptual models by which to explain customer behavior in financial technology-based platforms and to gain a deep understanding on customer decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al., 2022). Research studies on the diffusion of financial technology and Robo-advisors to customers are predominantly grounded on these three adoption models (Atwal & Bryson, 2021).

The Theory of Planned Behavior (TPB) was developed by Ajzen (1991) as a prediction tool for intention to behave in a specific manner, assessing attitudes toward the behavior, subjective norms, and perceptions of being in control. In TPB, individual social aims are planned by disposition, abstract standards, and conduct control. TPB has been used to explain and predict behavior across various behavioral domains, including technology adoption (Ajzen, 2020). TPB was an extension of Fishbein and Adzen's (1975) theory of reasoned action to explain the relationship between attitudes and behaviors within human action. Both theories have been used to understand the acceptance of Robo-advisors (Wu & Gao, 2021) and the intention to adopt Robo-advisors in Malaysia among retail investors (Zheng et al., 2021)

An extension of TPB was developed by Davis (1985) and named the "Technology Acceptance Model" (TAM). Davis et al. (1989) suggested that TAM could explain that users' intention to use an information system is determined by perceived use, usefulness, and attitude toward use. Davis adopted the theoretical views of Ajzen and Fishbein's (1975) theory of reasoned action (TRA) to show the perceived usefulness and ease of use. The TAM underwent several evolutionary stages to TAM2 and TAM3 iterations. Venkatesh and Bala (2008) proposed the TAM3, including several moderators such as experience, voluntariness, and "anchor" constructs. Although TAM has shortcomings in omitting risk perception, the theory is one of the most widely adopted conceptual models in studying technology acceptance. TAM has been used and tailored to specific contexts of research studies such as that of Atwal & Bryson (2020) to understand antecedents of intention to adopt AI services for personal financial investment in Germany and by David and Sadea (2021) to understand Robo-advisor adoption in during the COVID-19 pandemic.

Finally, the “Unified Theory of Acceptance and Use of Technology” (UTAUT) was proposed by Venkatesh et al. (2003), which replaced the attitude construct in TPB and iterations of TAM and developed their theory using new constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions as key predictors in the adoption of technology. Gan et al. (2021) used UTAUT as their baseline theory to explore how retail investors adopted financial Robo-advisor in times of high financial risk. Atwal and Bryson (2020) used the UTAUT to understand to what extent the German investor is willing to use a Robo-advisor instead of a human advisor. In a recent paper, seminal author Venkatesh (2022) presented UTAUT as the underlying theoretical basis for future research on adopting AI tools.

Literature Review

Research investigating investors’ adoption of Robo-advisory services remains limited, perhaps because of its recent market introduction (Tsai & Chen, 2022). Kavuri and Milne (2019) highlighted seven research gaps needing further exploration regarding the adoption of financial technology, including 1) changing industrial structure and organization of financial services, 2) new forms of financial intermediation (alternative finance) such as loan-based and equity-based crowdfunding, 3) changing payments mechanisms including central bank digital currencies and the shift to a cashless society, 4) reaching vulnerable and excluded customers in both developed and developing countries, 5) computation, AI, and large-scale data processing in finance, 6) the relationship between the new financial technologies and financial regulation, and 7) identity, security, data privacy and their regulation in financial services (p. 23). An updated framework from Kaviri and Milne's compilation research on financial technology found gaps in research around ecosystem linkages between consumers, financial institutions, and fintech companies with AI usage and how value is created through AI interactions (Manser Payne et al., 2021).

The Financial Industry and Robo-Advisors: An Overview

Robo-advisors are digital interactive software platforms with intelligence to drive automated wealth management, or financial services management suggested activities (Tsai & Chen, 2022). The evolution of Robo-advisors has taken two paths: advisor-assisted or fully automated. The example of advisor-assisted covers the experience delivered with an interactive interface in an app usually integrated with an internet bank or insurance company, like Wealthfront and Lemonade. Robo-advisor delivers the customer experience through the client/prospect's interaction with the app (Scholz, 2021).

On the other end of the spectrum is a system that assists advisors, who then deliver the suggested actions through personal interaction and assisted content and links (Bhatia et al., 2020). The advisor still delivers the client experience via human interaction, but the Robo-advisor guides the interactions' type, frequency, and content. A hybrid experience also delivers some digital self-service interfaces and some advisor-delivered interfaces. Most major financial services companies like Morgan Stanley and Prudential have an advisor-assisted and hybrid set of options. The Robo-advisor assists the advisor, reaching out to the client with that guidance. The fully automated Robo-advisors have lower overhead costs, including employee and commission costs, and thus allow a lower minimum investment or purchase requirement, and therefore are having greater success at attracting millennials who want to continue to grow their portfolios, with average account sizes of $20,000 to $100,000 (Atwal & Bryson, 2021).

Robo-advisors have become one of the most important FinTech tools/capabilities, a centerpiece of the customer engagement-enabling facilitation that FinTech is all about (Akdeniz, 2022). Over the last 2 decades, Robo-advisors' technological advances have included methodical, regular, and relevant advice on terms set by the client – when what, how to engage, and often, who starts the dialog. The pandemic heightened the demand for customized, direct digital engagement and digitally-enabled advisor/agent connection as uncertainty about the economy and the employment market drove panic and the need for a reassuring way to get advice on demand at any time of the day or night. Convenient customer capabilities have been a significant factor in Robo advisors gaining a leap in adoption momentum (Scholz, 2021).

There are barriers to entry that have kept the start-up de novo banks and financial services companies out of the industry related to physical infrastructure support costs, such as brick-and-mortar branch costs and the work-life amenities that go with that (Brenner & Meyll, 2020). Barriers to entry are significantly reduced or non-existent with the Robo-advisor platform, allowing more providers aligned to niche and specific target markets to provide different combinations of Robo-advisory services and address different needs within target markets, including generational interaction requirements

(Cheng, 2022). Anshari et al. (2022) outlined research on creating a digital twin of a client or prospect as a foundation for the next generation of Robo-advisors. Robo advisors evolved from a primary electronic interface designed to suggest a basic set of website-based services as a complement to facilitate the human advisor relationship to a highly personalized, even-wearable interface with an AI-driven brain. Each interface can attain customer permission and location and even serves proactive offers based on past spending and investment behavior, purchases, and goals (Brenner & Meyll, 2020).

The evolution of Robo-advisors has been driven by a combination of customer and advisor needs and requests, hyper-growth in regulatory requirements, and the digital transformation of the financial services industry, started by the ATM, the digitization of the consumer experience, and a global pandemic lasting over two years (Gan et al., 2021). The continued growth has been carried along by comprehensive digital education and the convenience and ease of managing an investment or protection portfolio. From purchase suggestions and research to modeled portfolio asset allocation and return forecasts based on individual goals to other product cross-sell or upgrade suggestions or administrative services such as sales distribution or benefits payouts, tax management advice, and generational wealth transfer (Chhatwani, 2022).

Several key factors facilitated the growth and popularity of Robo-advisors (Fan, 2021). One was the overall evolution of Fintech capabilities that enable Robo-advisors. Robo-advisor capabilities include instant and scheduled money transfers and payments, identity authentication, instant video conferencing, and next-best-action recommendation engine platforms such as Salesforce Einstein. The education and acceptance/adoption of the evolving Robo-advisors by financial planners/advisors and insurance agents has gained momentum (Fava, 2022).

Research Contrasting Traditional Financial Advisors and Robo-Advisors

Human advisors are still the mainstay of the advisory delivery stream (Piehlmaier, 2022). Although not all advisors are or will use a complementary Robo-advisory tool to facilitate and automate engaging with and servicing their clients, the most popular model that has emerged is a hybrid model. In a hybrid model, the human advisory force is given a customizable, built-for-the-company application that can be delivered to their desktop, and a version can also be sent to their clients, allowing the advisor to set contact cadence preferences, targeting, and call/engagement alert rules and content delivery/use filters and preferences. This hybrid model gives the advisors/agents control over their client engagement management, a top priority for advisor adoption. Human advisors can make themselves available for full-service relationship management or can set up specific services as fully or partially automated with services that include trade or purchase transactions, money transfers, and distribution approvals (Au & Krahnhof, 2020).

The shift in expectations and needs of consumers and investors and the changing environment due to the impact of COVID-19 imply that financial institutions were nudged to adopt new approaches toward creating investor relationships and value delivery for retail customers (Akdeniz, 2022). Innovative technology within the financial services sector has been applicable for payments, loans, insurance, and investments. Modern information technologies and the implementation of an automated advisor, or

Robo-advisors, make decisions on behalf of the customer with fintech capabilities and analysis of investor profiles (Boratyska, 2019; Breidbach et al., 2020).

The Robo-advisory services industry is nascent, including within developed economies (Ben-David & Sade, 2020). Robo-advisors are increasingly becoming the popular way of investment because they offer portfolio management services online that do not call for interactions between the client and the manager of the portfolio investment through the Robo-advisor comes with different advantages in which one is not required to have investment knowledge. In contrast, it calls for lower management fees than conventional financial advisors (Atwal & Bryson, 2021).

Fisch et al. (2017) chronicle the emergence of the human vs. pure Robo-advisors and the hybrid combination following each delivery type in their research. The pure Robo-advisor is the single interface between the customer and the client. These pure Robo-advisors work well with digital/remote banks and other financial institutions with clients who do not need or want human interaction. These customers tend to come from younger demographics, such as Gen Z and Gen Y, as they have been raised as digital natives and are very comfortable navigating financial applications and managing their money and assets digitally (Dagar et al., 2020).

Robo- advisors' competitors rolled out their solutions or were forced to test their firm’s Robo-advisor solutions to save money and create client wealth and insurance sales growth efficiency, especially during the Great Recession and other periods of company restructuring (Greve & Meyer, 2021). The rapid pace of smartphone sophistication has also been a catalyst in driving the growth and adoption of Robo-advisors. The rise of the smartphone app economy to power the distribution of Robo-advisors has also led to their exponential adoption. Integrating video and chat into the Robo-advisor apps has created a trustworthy remote interactive platform rather than just a supporting tool to facilitate human relationships (Ben-David & Sade, 2020).

Creating Customer Value Through AI interactions in Financial Services

AI has been developed to the point of recommending what a client is likely to purchase and benefit from based on their past behavior, uses high-speed predictive models that look at past product purchase patterns of similar clients and predict the likelihood that given a purchase suggestion, a client will act on it (Darskuvienen & Lisauskiene, 2021). Date-driven responses for content/topic suggestions for when and how to engage with clients regularly satisfy a banking regulatory requirement and create automated ongoing contact management and education/engagement delivery benefit that helps the client with timely advice on critical topics. The newest AI tools allow clients to create their portfolio models, simulate different investment allocation or trade investment scenarios, and set up multiple runs with various economic risk conditions to support the client on what, how, and when to invest (Fava, 2022).

In investigating the effect of customers' service awareness and technology readiness on their intention to use Robo-advisors and emerging economies, Henkel et al. (2020) examined whether AI-based emotion recognition software can support service employees in customer emotion management. Taking a value creation perspective, Castillo et al. (2020) considered the consequences of AI-powered chatbot service failures, including financial technology support, investment, and banking support. Regulation.

Although AI brings many benefits, increasingly sophisticated technologies also increase the potential for abuse. Financial institutions are concerned with data ownership, consumer privacy, and cybersecurity (Truby et al., 2020).

Regulation must address these concerns, as uncontrolled innovation can have devastating consequences (Accenture, 2019). Regulation affects all areas of financial services, including banking, investment, credit scoring, and financial advice, improving trust and credibility and customer perceptions of value for Robo-advisors' implications and current limitations (Lightbourne, 2017). Guo (2020) highlights legitimacy issues concerning Robo-advisors, which they attribute to a lack of investor protection and information asymmetry. Scholars have investigated AI's role in increasing financial inclusion, with some focusing on the regulatory environment. For example, Truby (2020) discussed the design of regulatory and legal frameworks focusing on AI use and wrote those clear policies are needed to ensure fair and equitable access to finance.

Banks increasingly rely on AI to improve the customer experience and expand their use of AI through conversational chatbots to assist customers with essential services or virtual assistants (Guo, 2020). Most banks consider AI technologies beneficial to the institution in various ways, including increasing revenues through improved customer service and reduced costs due to enhanced efficiencies, lower error rates, and improved resource utilization (McKinsey and Company, 2020). Scholars have explored banking through the lens of the benefits and challenges of conversational software agents or chatbots (Adam et al., 2020) and how AI may alter bank employees' relationships with their customers (Boustani, 2021).

Although Robo-advisors provide numerous benefits, including service fee reductions and 24/7 consumer access, consumer adoption has been slow (Brenner & Meyll, 2020). Bhatia et al. (2020) investigate whether and how Robo-advisors could mitigate retail investors' behavioral biases. Brenner and Meyll (2020) found that Robo-advice reduces the demand for human financial advice, especially for investors who fear investment fraud. Similarly, Atwal and Bryson (2021) explore private investors' Robo-advisor adoption intentions, whereas Fernandez & Oliviera (2021) investigated the effect of customers' technology readiness on their intention to use Robo-advisors.

Taking a value creation perspective, Castillo et al. (2020) considered the consequences of AI-powered chatbot service failures, including financial technology support, investment, and banking support once AI is introduced to a digital self-service channel. AI-based emotion recognition software can support service employees in customer emotion management. Consumers perceive AI's problem-solving abilities with service delivery and the customer's value co-creation role change, while others find that (Castillo et al., 2020). Payne et al. (2021a; 2021b) investigated customer value creation/destruction outcomes by investigating antecedents of customer resource losses and value-in-use perceptions of AI-based mobile banking applications. AI and chatbots do create value, especially from a technological perspective (AI and leveraging customer data), theoretical perspectives (service logic and customer data as a resource), and industry phenomenon (transfer of resources and processes/digitalization) (Hentzen et al., 2021).

Factors Driving Investors in Western Financial Markets to use Robo-advisors

The launch of Robo advisors as a concept can be traced, according to Phoon and Koh (2018), to the parallel rise of electronic trading and digital banking as a broad category. The constant pressure on the industry to continually bring on new customers, serve them rapidly, and keep up with aggressively growing sales goals created conditions in the investment banking sector especially. The rapid pace nature of the industry, with constant innovation around wealth management, financial planning, and investment products, creates a natural environment for necessary disruption and new ways of finding, engaging, and retaining customers (Brenner & Meyll, 2020). The other factor that has propelled the adoption of Robo advisors in the investment industry is the need to predict and manage the behavior of clients and their assets. The quantitative nature of the industry, and the rise of predictive modeling, machine learning, and AI as newly emerging management tools to target which, when, where, and how to engage with and offer the most relevant advice and set of recommendations and investment products (Hentzen et al., 2021).

The uses, as outlined by Phoon and Koh (2018), spring from the market and Wall Street's relentless pressure to squeeze every drop of efficiency from the management of the customer lifecycle, from initial investment to asset reallocation and portfolio balancing and management, as well as cross-sell up-sell and client retention and referral. The other set of user-driven needs that have been a catalyst to the application of Robo advisors in the US is efficient workflow management for advisors/agents and their teams. The workload of administration and compliance tasks is frequently overwhelming without some automated and streamlined help. The equity and mutual fund trade registration and clearance proper recording and retention alone are enough to completely take up the time of a support team (Guo, 2020).

According to Piehlmaier (2022), the age factor is the single and most significant adoption driver for Robo-advisors. Reading deeper into the analysis, the real driver is the desire to make money because one has his/her whole life ahead to recoup any losses and is not as afraid of risk-taking. This is where the overconfidence driving the adoption of rob-advisors comes in. The quantitative analysis of 2,000 investors who completed an investment behavior and satisfaction survey was analyzed. The findings from a generalized linear model show that increased financial knowledge and literacy decrease the likelihood of adopting a Robo-advisor. However, in a contradictory finding, the model findings also support that increased financial risk-taking is associated with using a Robo-advisor, as is having strong confidence in one’s financial knowledge. Oehler et al. (2021) paint a similar portrait of financial savvy guiding the precise use of Robo-advisors for stock and bond investing but highlight the trust and human connection/friendship with an advisor as a specific obstacle to using a Robo-advisor. When a long-standing and deeply trusted relationship exists between the human advisor and the client, one that well supersedes the introduction of the Robo-advisor software, the software is not considered since the client enjoys close and frequent personalized communication and advice discussion.

Piehlmaier (2022) also suggested that the persona of someone most likely to adopt a Robo-advisor is a young person (under 40) who is egotistical, greedy, and anxious to make money as quickly as possible, and has not experienced the painful consequences of a significant financial loss made from a quickly made decision. The author further emphasized the US investment market as the center of Robo-advisor investment, with 50% of all invested funds coming from the US. It is essential to understand the motivation and behavioral drivers of the US Robo-advisor investor across the product adoption lifecycle to develop a value proposition and product delivery strategy that will accurately predict the persona description, size, and speed of adoption for each segment applied to the Robo-advisor community globally. Ben-David & Sade (2020) added a critical dimension to the fact that during a crisis such as the COVID-19 pandemic, Robo-advisor adoption is likely to increase as the need for quick, easy, reliable access to advice/an advisor is far more critical than the type of advisor. Hence, customers become less picky about how the advice is delivered. Once the crisis is over, the barriers to adoption increase and the type of advice sought shifts to focus on trusted human interaction.

Belanche et al. (2019) emphasize the importance of Robo-advisor interfaces designed to address the needs of the users and to create a delightful, simple, and easy user experience and underscore Piehlmaier's (2022) point on the need, and lack of a body of research, on understanding and describing the range of motivational, demographic and behavioral drivers based on US investor behaviors. Therefore, given the lack of a compendium of in-depth behavioral research to support the successful adoption-at-scale, and a broad expansion of Robo-advisors in the finance industry, there is a need to develop a comprehensive model that better explains the critical perceptions and motivations driving Robo-advisor adoption by a wide range of customers. To do so, and based on well-established technology adoption theories, the authors propose a framework wherein perceptions about a Robo-advisor's usefulness and ease of use, together with consumer attitudes, impact the intention to adopt this service (Guo, 2020).

Since Robo-advisors are disruptive change agents and new technology, there are varying degrees of exposure, experience, and willingness to adopt Robo-advisors (Guo, 2020). The study, therefore, highlights a gap in the research and the need for segmented Robo-advisor adoption research by traditional demographics such as age, gender, race, experience, exposure, and willingness to use Robo-advisors and technology in general. The study also touches on the need to understand social media and other contextual societal influence factors, including ethical and legal factors such as availability/accessibility and socio-economic barriers, presumably also by those same experiences, exposure, and willingness to use Robo-advisors (Belanche et al., 2019).

Reuter and Richardson (2016) delve into the delivery side of Robo-advisor adoption and outline the factors that influenced advice-seeking, which Robo-advisor uses to build defined contribution retirement portfolio growth across 23 companies. The authors found that advice-seeking increases with age, account balance, annual contribution level, web access, and changes in marital status. Paradoxically, the introduction of Robo-advisors increased advice seeking significantly, presumably due at least in part due to the ease of access through the Robo-advisor interface. However, the authors also found that reliance on default asset management frameworks reduced investment advice-seeking significantly. Advice-seeking retirement portfolio investment management is only weakly correlated with market returns, clouding the value proposition case for personalized investment advice and one of Robo-advisors' primary value drivers (David & Sade, 2019).

David and Sade (2019) investigated the willingness to pay and trust financial management advice and compared readiness to adopt and willingness to pay for (as a proxy for trust) financial advice provided three ways (algorithm, human, and a hybrid of algorithm and human) using an online and a controlled experiment. The authors tested different types of advice, from in-person to Robo-advice to a hybrid, and the willingness to pay a fee to consume those types of advice as a proxy for trust. They found that younger participants between the ages of 20 and 30 years are willing to pay more for algorithmic than human advice. Adding the hybrid option lowered their willingness to pay for this same age group. Among financial services customers, an integrated delivery service model is significantly more efficient and effective at supporting holistic value delivery (Li et al., 2017).

Participants between the ages of 31 and 44 years are willing to pay more for the advice from the hybrid model than the algorithm and a similar amount for the hybrid and human advice (David & Sade, 2019). The age group of 45-year-olds and above exhibits a nonsignificant tendency to adopt the algorithmic compared to the human advice but adding human assistance reduces their willingness to pay. The study found similar results as other previous studies that men are ready to adopt and pay more than women for financial advice in general. Those differences derive primarily from the algorithm advice alternative and after controlling for a vector of technology adoption constructs, financial literacy, quantitative knowledge, and personal and demographic proxies.

According to Warchlewska and Waliszewski (2020), having a robust user profile, including demographics, risk tolerance, and building on previous relationship interactions and customer history, allows for a better, more relevant offer and content targeting and more ethical engagement, which are the factors that drive Robo advisor use. "Know me, understand me, customize for me" based on my entire profile is the primary use finding. Creating a rigorous process to capture a complete picture of a prospect or customer's demographics, priorities, station in life, needs, values, and attitude are all keys to driving adoption.

Customer Value Delivery at Financial Institutions

Customer value delivery appears to be at a low level in banks, and their services are not enough for the customer, who only sees banks as not meeting the holistic value required from the customer's point of view (Scholz, 2021). As measured by the ACSI (2021), value delivery in financial services has been hovering around 72% for over twenty years. Customers are not finding increased value delivered by the significant technological advances over the past twenty years. This highlights the value delivery gap between financial institutions and their customers. In customer-focused front-office applications, the bank customer will play a crucial role in the adoption intention of Robo-advisors (Greve & Meyer, 2021).

Komulainen et al.(2018) highlighted their hypothesis on the reason for the value delivery gap. They observed through their research and meta-analysis of the value delivery topic that banks do not clearly understand customers' real needs and value drivers because they do not spend the time researching them. Instead, they are focused on driving efficiency and cost savings for operations. Customers do not feel their banks care about understanding their barriers to adoption and what they want in terms of personalized value delivery. The authors point out a significant research gap due to a lack of in-depth research specifically around mobile banking-specific value creation- tailored offers and services that will attract customers to use their app but will make it easy for them to do so (Hildebrand & Anouk, 2021).

Komulainen et al. (2018) also found that the basic framework of what customers value is an integrated, comprehensive approach to the services that probably cannot be handled by one provider because of the complexity of the range of desired services from different customer experience segments. According to the author, customers need much deeper personalization that mimics a trusted private banker concierge who understands their specific life situations and challenges. That kind of specific life recommendation takes deep AI development. Adam et al. (2020), with their focus on chatbot research to drive greater engagement and use of them for customer service interactions mainly, have discovered that infusing anthropomorphism and especially human emotions without trying to pretend that the Robo-advisor (in this case, the chatbot interface) is a real human being, does improve engagement per their controlled experiments.

Piehlmaier (2022) wrote that a robust set of capabilities to interact with customers via expansion of the ability to make small talk, add empathetic responses, and add humanistic response times that build in pauses when complex topics are raised instead of sending a pre-canned answer immediately back. A key goal is to give a strong, contextual social presence feeling, which includes greeting with a personal message, referencing last interactions, and other important life events or experiences. Hildebrand and Anouk (2021) underscore the importance of conversational, personalized Robo-advisors, again using everything known about the customer or prospects to create as human an interface as possible with relevant and inviting conversational responses to engagement, and capturing, learning, and incorporating more needs, attitudes, values, and life journey details to drive the interactions.

Catillo, Cahoto, and Said's (2020) work on uncovering details around what interactions or other factors destroy value further provide more specifics on the kind of interactions that cause customers to disengage when interfacing with a service chatbot. The lack of a relevant and targeted response to the first question seeks to capture and correctly understand/process the customer's issue or question. The first response is critical to respond with a relevant, socially salient, and empathetic response and a follow-up series of questions. If that initial connection was not correctly made or perceived as such, or there was a technical glitch, such as asking the same question twice in a row, the customers were much less likely to perceive value and social contextual awareness from the chatbot. Then the majority of the time, they abandoned the chatbot interaction, telling themselves that they did not need support that badly since they did not view the chatbot interface as trustworthy or capable (Guo, 2020).

In further researching how customers react to AI failures, Huang and Philip (2020), who delivered the only study on AI failures reactions so far, found that the use of specific individual past behaviors to drive a personalization engine that created highly customized messages using past customer service interactions, company interactions, life events, and milestones, created meaningful connections with customers, even if later in the interaction, the service experience failed to resolve the issue or otherwise meet satisfactory service resolution. Another critical factor is the cost of the advice. To the extent that the cost of Robo-advice is significantly cheaper than the cost of in-person advice, the demand for advice was found to increase for those investors not following the default option (Reuter & Richardson, 2016))

Intention to Adopt Robo-Advisor Services by Consumers in Personal Investing

Understanding drivers of Robo-advisor adoption intention are just beginning to be understood. Several early necessary global studies from Gan, Khan, and Liew (2021), Menon and Ramikrishnan (2021), and Bhatia et al. (2021) have laid and initially outlined the adoption factor framework and are outlining a blueprint of crucial usage intentional factors and attitudes. The pandemic also had a significant catalytic effect that is both helpful and non-typical, so the context and timeframe of the studies as to how the pandemic influenced their intentions since the conditions of the pandemic forced the use of Robo-advisors for many consumers. Now that we are emerging from the pandemic, it will be necessary to validate the during-pandemic Robo-advisor intentions and drivers post-pandemic. To lay a foundational framework during the literature review, we will assume that the findings attained during the pandemic will also apply post-pandemic.

The empirical framework was established by a study in Asia that measured behavioral intentions to use Robo-advisors to manage a portfolio of a consumer's investments. Gan et al. (2021) used UTAUT (unified theory of acceptance and use of technology) as a foundation to develop an intention driver hypothesis framework, and developed a seven-factor model to validate usage factors on actual Robo-advisor use during the pandemic in Malaysia. The seven factors were 1) performance expectancy- the expectation that Robo-advisors would improve financial performance, 2) effort expectancy (ease of use), 3) social influence (Robo-advisor use opinions and esteem/importance by social network of family and friends), 4) facilitating conditions (the circumstances that make it necessary such as the pandemic where in-person contact was prohibited, or likely that use of a Robo-advisor will be easy and helpful 5) trust in Robo-advisors/Robo-advisor technology 6) perceived financial knowledge (how much a customer thinks they know about financial services, not how much they have been assessed by outside objective testing as knowing 7) previous tendency to rely on Robo-advisors.

Gan et al. (2021) interviewed over 286 banking customers who owned investment portfolios and had prior exposure to Robo-advisors. The authors found that the strongest usage intention factors correlated to the consumer's stated intention to use a Robo-advisor were trust in Robo-advisor technology, previous use of a Robo-advisor, and perceived solid financial knowledge. Secondary usage intention factors with secondary, less impactful supporting factors for using a Robo-advisor are positively correlated with use being improved performance expectations, social influence, and facilitative conditions. These findings aligned with the UTAUT foundational empirical paradigms that assert that consumers who gravitate toward using financial technology are more educated, experienced, and confident about the application of technology to manage their financial assets and expect it to enhance their financial portfolio performance. Additional studies used and validated the technology acceptance model based on the same theory. Menon and Ramakrishnan's (2021) work is also grounded in theories like the Theory of Planned Behavior (TPB) and the Motivational Model theory; both are used to determine the linking factors between thoughts, attitudes, and behavioral motivation.

Another intense, well-designed Asian behavioral usage and attitude corollary study provided linkage evidence between thoughts and behaviors. Menon and Ramikrishnan’s (2021) work in India to understand the factors that drive Robo-advisor adoption in wealth management reinforces the Gan et al. (2021) study. The Indian researchers' study confirmed the importance and significance of similar factors on behavioral intention to use Robo-advisors: trust (described as attitude toward Robo-advisors), confidence in financial knowledge, previous use of/comfort with the use of Robo-advisors (described in this study as self-efficacy), and ease of use. The Indian authors focused on gathering and analyzing the attitudes, liking, conception, and acceptance factors of Robo-advisor adoption across 321 investment banking customers of institutions across major cities in India.

Menon and Ramikrishnan's (2021) studied the impact of attitude on behavioral intention to use a Robo-advisor in wealth management, adding a dimension of understanding how the use intention decision is made versus other studies that focused just on the intention to use. There was a counter-intuitive finding that there was a negative relationship between intrinsic motivation and intention to use Robo-advisors. It is hypothesized that given the relationship-intensive wealth management advisory industry, the advisor or customer has a resting lack of desire to replace that relationship with a computer-interface-based tool. Therefore, the other outlined factors have to wield an even stronger significant impact to shape the intention to use Robo-advisors (Menon & Ramikrishnan, 2021).

Robo-advisory adoption cannot gain momentum unless potential users know what adoption looks like. Bhatia et al. (2021)'s research goal was to understand the factors that precede adoption. The goal is to understand and better describe Indian wealth management customer awareness, consideration, and perception of Robo-advisors, before understanding the factors that drive adoption. The authors outlined the following factors to consider Robo-advisors: cost-effectiveness, trust, data security, overall past use of and comfort with technology, and financial and overall need circumstances of the investors. Active investors observed these as significant factors influencing the awareness, perception, and consideration for using Robo-advisors (Menon & Ramikrishnan, 2021).

The predominance of the investors surveyed viewed Robo-advisors as appropriate only for quantitative suggestions (e.g., how much money to invest in different types of instruments) and wanted a human advisor explicitly overseeing the Robo-advisor interaction in order even to begin to consider using the technology in a routine and regular basis (Bhatia et al., 2021). The net conclusion of the study was that Robo-advisors were not a stand-alone solution for the Indian wealth management market. Atwal and Bryson (2021) found similar factor priorities in their work on Robo-advisor antecedents. The investor participant feedback from Germany also raised the question of to what extent investors' were willing to use Robo-advisory services instead of a human advisor to manage their investments.

The qualitative research identified similar constructs as significant drivers in the emerging body of the Robo-advisor adoption construct framework. The work that impacts the intention to use AI to invest: perceived risk, perceived usefulness, perceived ease of use, social influences, and intention to use. The work of Menon and Ramikrishnan (2021), Bhatia et al. (2021), and Gan et al. (2021) distilled similar factors and findings. Whether in Asia or Europe, the familiar drivers of Robo-advisor adoption that need to be met to sustain meaningful use are targeting educated, tech-savvy investors who have strong confidence in their financial knowledge, providing easy-to-use interfaces/applications, and most importantly, delivering trusted advisory branded experience that wraps around the user experience.

Summary and Conclusions

In Chapter 2, I conducted a thorough literature review and critical analysis of scholarly research on the core concepts of Robo-advisor adoption by retail customers. Customer value delivery appears to be at a low level in banks, and their services are not enough for the customer, who only sees banks as not meeting the holistic value required from the customer's point of view. Aligning with the study's purpose, The Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) can provide a framework of theories and conceptual models by which to explain customer behavior in financial technology-based platforms and to gain a deep understanding on customer decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022). The literature search identified key, defining terms, and specialized journals and databases were used for the literature review.

The Robo-advisor is an AI-driven virtual financial advisor that provides investors access to low-cost products and high-quality financial advice (Wexler & Oberland, 2020). Traditional financial advisors help the customer by assessing their needs and objectives, defining their level of risk, and investing their customers' money according to this risk (Scholz, 2021). For retail investors, the Robo-advisor has gained considerable attention and has become a growing trend to outnumber traditional financial advisors with benefits due to lower charged fees, ease of use, and diversified services (Bhatia et al., 2020; Brenner & Meyll, 2020). While using Robo-advisors in financial institutions has become a popular trend, early adopters' socio-psychological barriers may thwart the long-term success of this AI application to long-term use (Merkle, 2020; Tsai & Chen, 2022).

While banks are set to invest heavily in developing AI value-driven competencies, the successful adoption of Robo-advisors within the financial services industry will depend on gaining a critical understanding of the customer’s potential barriers to AI adoption. The value delivery gap between financial institutions and their customers. In customer-focused front-office applications, the bank customer will play a crucial role in the adoption intention of Robo-advisors Finance and information technology scholars identified a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments. My literature review in this chapter presented what is known about the adoption intentions of retail investors across Western financial markets to use a Robo-advisor instead of a human advisor and what more scholars and practitioners need to learn on the topic.

In the next chapter, 3, the methodology will be presented using the qualitative research method for this study and a case study approach. Additionally, the research design and rationale, the researcher's role, the methodology of recruitment, and participation and data collection will be presented in chapter 3. Finally, the data analysis is included in chapter 3 and will address the questions of trustworthiness and ethical procedures.

Chapter 3: Research Method

The purpose of this qualitative, single case study with embedded units was to understand the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor. I used a single case study with an embedded unit design to address this gap within the qualitative paradigm (Yin, 2017). Understanding the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor may inform marketers to what extent American investors are willing to use Robo-advisory services instead of a human advisor to manage their retail investments.

Following Atwal and Bryson's (2021) recommendation, future replication studies of their qualitative research were needed in other Western markets to validate their preliminary findings on the adoption intention of Robo-advisors in Germany. Finance and technology scholars remained uncertain about how far the Robo-advisor trend will continue due to early customer adoption barriers and challenges (Bhattia et al., 2021). By further understanding retail investors' adoption intentions in using a Robo-advisor, this study's results may drive positive social change by offering pathways to very low-cost, automated financial management advice to a broader segment of new and intermediate investors (Atwal & Bryson, 2021).

This chapter provides detailed information on the research method and rationale for conducting a qualitative single case study with embedded units. The central research question (CRQ) guiding this empirical investigation is presented along with the participant selection strategy, data collection strategies and data analysis, the researcher's role, ethical considerations, and a summary of the main points of Chapter 3.

Research Design and Rationale

The research question drives the research strategy (Browne & Keeley, 2014). A researcher must identify the right question for the study. Consistent with the purpose of this study, the CRQ is as follows:

How do retail investors in U.S. markets describe their adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor?

Traditional financial advisors face challenges brought about by the increasing presence of Robo-advisor- based services (Fisch et al., 2019). Successful traditional client-facing financial advisors develop deep relationships with clients over time, invest more time in providing services, and utilize quality administrative and executive support to manage and operate their advisory firms (Fan & Chatterjee, 2020). For retail investors, the Robo-advisor has gained considerable attention in financial decision-making and has emerged as an effective alternative to traditional financial advisors with benefits including lower charged fees, ease of use, and diversified services (Bhatia et al., 2020; Brenner & Meyll, 2020).

The literature has said little about adoption intentions that drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). The qualitative method was appropriate for this study because it aligned with my purpose: to explore the adoption intentions of retail investors across Western financial markets to use a Robo-advisor instead of a human advisor. A mixed-methods approach was inappropriate because quantitative data do not answer a qualitative research question (Harkiolakis, 2017). The qualitative method supported my generating information about human interaction within a natural setting and analyzing data inductively (Stake, 2010).

The research design proposed for this study was a case study using five to 10 in-depth interviews. A case study approach was broad enough to provide the flexibility needed to extend a theoretical model (Norlyk & Harder, 2010). Extending a theoretical model may be ineffective through a design like narrative inquiry and its storytelling approach or phenomenology's central theme of finding the meaning of lived experiences. Grounded theory is used when the theories resulting from the study are a unique outcome of the data analysis from the study (Merriam & Grenier, 2019).

Instead of using hypotheses, the case study researcher may develop "theoretical propositions," which are used to drive the data analysis of the case (Yin, 2017) and are grounded in the literature, theories, and analysis of empirical data. Yin (2017) recommended that "the case study method is pertinent when your research addresses either a descriptive question (what happened?) or an explanatory question (how or why something happened?)" (p. 112). New knowledge emerges from a single case study when patterns in the collected data, its analysis, and the logical arguments that underpin them emerge after a rigorous empirical process (Eisenhardt & Graebner, 2007).

Role of the Researcher

I was not a participant in this research but rather a researcher investigating the study's purpose and answering the central research question. My role in this qualitative research was critical, and the researcher is considered an instrument engaged in collecting, analyzing, and presenting the results (Denzin & Lincoln, 2011; Maxwell, 2013). As an instrument, the researcher can be the greatest threat to the trustworthiness of the final results if they are not aware of their issues with reflexivity (Tracy, 2019).

As the author, I was responsible for designing and delivering the end-to-end primary research process, including creating the research framework and plan, completing the interviews, and qualitative coding and analysis (Halkias & Neubert, 2020). I ensured that the data collection instrument and process were free from instrumentation, interview, and analysis bias. I ensured the validity of the process through verification and peer/committee review (see Tracy, 2019).

As the author and researcher, I ensured the process had integrity end to end, including checking for integrity and watching for bias during the design, data capture, recording, interview coding and analysis, conclusions, and recommendations that add new original knowledge. I will be direct, open, and honest in explaining how I designed, collected, categorized, assimilated, and distilled insights in the research process, following peer-reviewed best processes (Polit & Beck, 2014). I documented every step of the research process, recorded the end-to-end data collection and management process, and reviewed it with my committee to ensure control of bias and process management integrity (Berger, 2015). My duty as an objective researcher is to ensure that the participant answers, or my analysis and distillation of conclusions, are not influenced by bias (Saldana, 2016). I kept in mind that my research position is an observer, recorder, and qualitative data analyst throughout the process (Chesebro & Borisoff, 2007).

Methodology

This research aimed to gain a deeper understanding of the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor. This exploratory case study's purpose may have addressed the literature gap on understanding what factors drive investors in Western financial markets to use a Robo-advisor to manage their investments (see Piehlmaier, 2022; Zhang et al., 2021). Following Atwal and Bryson's (2021) recommendation, future replication studies of their qualitative research will be conducted in other Western markets to validate their preliminary findings on the adoption intention of Robo-advisors in Germany. I used a single case study with an embedded unit design to address this gap within the qualitative paradigm (Yin, 2017). A quantitative method was inappropriate for this study since my aim was not to measure relationships, test theories statistically, and collect quantifiable data. (Harkiolakis, 2017).

Yin (2017) stated that a case study might be a person, event, entity, or another unit of analysis. The case and embedded unit of analysis in this research will be the retail investor. A single case study intensively emphasizes an investigation and analysis of a unit embedded in a case (Hancock & Algozzine, 2016), enabling a researcher to contribute significantly to the existing knowledge by extending the theory (Yin, 2017). Case studies offer a chance to get a snapshot of real life, and this research design helps explore a complex topic from which contrasting results have emerged from previous studies or for designing a replication study (Halkais & Neubert, 2020).

Qualitative research uses purposeful sampling strategies to recruit information-rich cases related to the phenomenon of interest (Palinkas et al., 2015). I conducted 10 semistructured online interviews with retail investors in U.S. markets**,** meeting the study's inclusion criteria. Multiple data sources were collected, including reflective journal notes and archival data from media sites on the adoption and use by customers of Robo-advisors within the US financial services industry (see Stake, 2010). Data from multiple sources, such as participants' experiences, generated a whole picture of the phenomenon (Merriam & Tisdell, 2015).

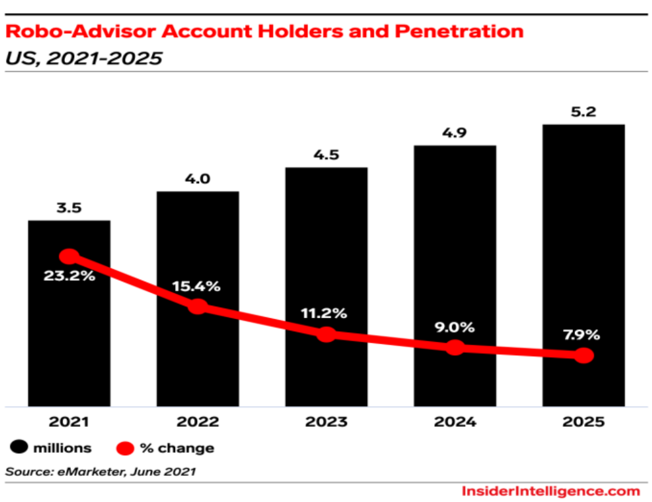
To meet the Walden Ph.D. dissertations standards for sample size, I conducted five to 10 online, semistructured interviews with U.S.-based retail investors, with the final sample size determined by data saturation within the interview data (Merriam & Grenier, 2019). I planned to conduct 10 in-depth online interviews using the Zoom platform with my study participants (see Gray et al., 2020). Selecting a range of five to 10 participants for a qualitative study is recommended, as a larger sample size may weaken an in-depth investigation of the phenomena under study (Schram, 2006).

The participant selection logic aligned with technical and strategic case study requirements (Yin, 2017). To appropriately validate the credibility of the results and protect the integrity of the process analysis and synthesis, the collection process included multiple sources, including in-depth interviews, literature review notes, journaling observations, and historical data, to recommend additional suggestions for additional research (Guion et al., 2011). Stake (1995) observed that while using a qualitative approach, the more evidence that is reviewed, the stronger the insights will be that are distilled from the multiple perspectives gathered.

Participant Selection Logic

The target population for this case study was active financial services customers who owned a smartphone and computer and could have used it to manage their finances with the option of a Robo-advisor to assist. In 2021 in the United States, 3.5 million adult investors used a Robo-advisor to handle their portfolio, up by 23% over 2020, which saw the then most significant adoption growth of 37%. The growth rate in the United States will stay in the double digits for several years, putting usage on pace to surpass 5 million adults by 2025 (see Figure 1; Insider Intelligence, 2021).

Figure 1



Purposeful and criterion sampling was my selection strategy because it enabled choosing participants who could provide rich information relevant to the research questions (Maxwell, 2013; Palinkas et al., 2015). Purposeful sampling was used in qualitative research to recruit information-rich cases related to the purpose of the study (Merriam & Tisdell, 2015). Purposeful samples are generally small. I also used snowball sampling, which helped me identify other participants who meet the selection criteria by asking identified key participants to refer other potential participants for the study. (Merriam & Tisdell, 2015). Participants recruited from participants who have been accepted to the study ensured I could identify quality participants who might be challenging to find using other sampling strategies (Noor, 2008).

Participants for this case study were recruited using purposeful sampling strategies and screened with the following inclusion criteria: a) adults over the age of 18 residing in the United States; b) 1 year of experience using a Robo-advisor for retail investing; and c) possessed knowledge and experience using a traditional financial advisor for investing their money. The study sample's inclusion criteria replicated inclusion criteria from similar studies (e.g., Atwal & Bryson, 2021; Bhatia et al., 2021). Potential participants who did not meet the inclusion criteria were excluded from the recruitment list. I conducted five to 10 online, semi structured interviews with adults in the United States using the Zoom video application (see Gray et al., 2020). Schram (2006) recommended that qualitative researchers recruit between five to 10 participants because a larger sample size can lead to weaker research results and compromise in producing detailed, thick descriptions of the participants' experiences using a Robo-advisor for retail financial investments.

I used the LinkedIn professional network as a recruitment platform for my research. Using the LinkedIn network allowed me to receive responses and feedback from many professional practitioners (Stokes et al., 2019). Using LinkedIn helped me to target specific participants in a particular field through professional groups on the platform. I emailed the pre-screen participants and sought their interest in participating in the study. The final sample size was determined by data saturation ad upon review of the transcripted manuscript (Merriam & Grenier, 2019). Data saturation may be attained by as little as five interviews, depending on the population's sample size; large sample sizes do not guarantee that one will reach data saturation (Halkias & Neubert, 2020).

Instrumentation

Instrumentation in a case study collects qualitative data from multiple sources and provides appropriate data collection instruments to answer the research question (Yin, 2017). Instrumentation protocols aligned with my study's purpose contributed original qualitative data to the conceptual framework. Careful development of appropriate data collection processes allowed themes and insights to emerge from the study results from studying and understanding retail investors' adoption intentions in U.S. markets to use a Robo-advisor instead of a human advisor. Three sources of data were utilized throughout this study: (a) a semistructured interview protocol (see Appendix B) whose items have been designed and standardized by previous researchers, (b) archival data in the form of government and widespread media reports (Yin, 2017), and (c) reflective field notes (Merriam & Tisdell, 2015), which I kept throughout the interview process.

The Interview Protocol

The interview guide for this study (Appendix B) consisted of semi-structured questions adopted from interview questions developed by Atwal and Bryson (2021) and Bhattia et al. (2021) when interviewing retail investment customers on Robo-advisor adoption in Germany and India, respectively. The interview protocol (Appendix B) was used to collect qualitative data on understanding the adoption intentions of retail investors in US markets to use a Robo-advisor. The interview protocols were both an open-access document, and the interview protocol questions were piloted and validated (Atwal & Bryson, 2021; Bhatia et al., 2021); therefore, not needing another field test conducted to test the validity of the interview questions items in the meeting the purpose of the study. Validation was necessary but not critical to qualitative research, as concepts invariably reflect the realities of the study's context (Merriam & Tisdell, 2015).

This study utilized a similar conceptual lens used by Atwal and Bryson (2021) and Bhattia et al. (2021), thus supporting their interview items as a replication study. The interview questions used in this study are grounded in the theoretical literature and Atwal and Bryson's (2021) and Bhattia et al.'s (2021)insights into the study topic. This study's interview protocol was consistently grounded with this study's conceptual/theoretical framework: The Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) provided a framework of theories and conceptual models by which to explain customer behavior in financial technology-based platforms and to gain a deep understanding on customer decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022).

The semi structured interview strategy supported a contextual understanding of how a phenomenon develops and is applied (Tracy, 2019). Hence, using probing and exploratory, semi structured interview questions in this type of case study was valuable to give a perspective into each participant's experiences to facilitate the transferability of study results to other contexts. Transferability challenges qualitative researchers because it limited findings to given sample groups and their contexts. Designing a disciplined and thorough study improved the transferability and credibility of study results to allow greater transferability across different industries and disciplines (Stake, 2010). The interview protocol used probes to facilitate conversations regarding the facts, such as "Can you give me an example?" and "Please tell me more about that." Probing questions can encourage detailed responses on specific topics customized to the participants' narratives (Merriam & Tisdell, 2015).

Archival Data

Archival data can be any information previously collected by others and is available for systematic study and a source of data collected within the case study design (Yin, 2017). I reviewed and annotated peer-reviewed scholarly papers from at least 100 scientific journals during this process. I gathered this archival data and created a database containing information from the popular press and social media sites regarding customer adoption of Robo-advisor services for retail investors. These reports were substantive for the literature review and served as a data triangulation source to complement the semi structured interview data and reflective field notes.

Reflective Field Notes

The third instrument to gather data from the research participants was the assembly of netnographic field notes derived from semistructured interviews conducted via the Zoom platform (see Kozinets, 2017). Zoom enabled the interview interaction to avoid contextual information influencing the researcher to avoid personal reflexivity and maintain a significantly unbiased atmosphere (Gray et al., 2020). Reflective field notes may reveal more than observational field notes because online data interactions are usually not recorded while occurring and, as such, reflect a written database of researcher observations concerning subtexts, pretexts, contingencies, conditions, and personal emotions occurring during the semi structured interview (Morgan et al., 2017). This netnographic field note process revealed critical details concerning online social interactions' functioning to decode cultural actions' explanations relative to providing a more detailed description (Kozinets, 2017). This reflective field note method has been used in similar studies such as Sadvandi and Halkias (2019) and Stone and Harkiolakis (2022), where case study researchers used observational research methods to explore the research questions within real-world settings (see Yin, 2017).

Procedures for Recruitment, Participation, and Data Collection

I launched and managed the recruitment process after obtaining formal approval from the Walden University Institutional Review Board (IRB), advising me to continue conducting the research. I sent an introductory LinkedIn message or email invitation to potential participants identified and pre-screened from the LinkedIn platform on social media. Compared to traditional recruitment methods such as flyers, newspaper adverts, letters, emails, and word-of-mouth, social media provides greater visibility and is a cost-effective and faster recruitment method (Stokes et al., 2019). The participants were made aware of the study's aim, participation duties, and all other information that ensured they participated based on an informed decision through my initial recruitment letter. (Robinson, 2014).

I attached the informed consent and demographic forms to a follow-up email. The demographic forms provided the participants' age range and did not include the exact age to protect their privacy. The informed consent explained the nature and purpose of the study, the risk and benefits of being a participant in the study, and the potential positive social change resulting from the study. The informed consent stated that participation is voluntary, that participants could withdraw their participation from the study at any time, and explained and committed to how their privacy will be protected by ensuring confidentiality and anonymity throughout the research process.

If they elected to participate, I requested the participants express their consent by responding to the email with the words "I consent" and their availability to participate in an interview, thus commencing the interview process and engagement in the study. I then prepared an interview guide and timeline based on their agreement and participation availability. I developed a set of semi structured interview questions based on the conceptual framework noted in the literature review to understand the extent to which the participant used Robo-advisors, the technical and psychological reasons for the use, and the barriers preventing the ideal use. Semi structured interviews offer an opportunity to address the primary research question and additional insights from participants (Manhas & Oberle, 2015).

Each semi structured interview on Zoom or over the phone was scheduled for 30 minutes, in which 5 minutes were used to verbally review the purpose of the study and the informed consent. The interview was conducted in a safe, quiet, and relaxed setting, free from distraction. During the interview, I asked open-ended and probing questions. These questions allowed the participants to provide depth and detail and clarify ambiguities (Rubin & Rubin, 2011). I took notes of participants' responses and observational cues during the interview to gain a more in-depth insight into the participant's views (Seitz, 2016).

The interview was recorded if the participant consented to be recorded, and I also took notes during the interview, allowing non-recorded interviews that were taken from notes only. Once the interview was complete, I saved the audio recording and secured the file with encryption and password protection on my laptop's hard drive. The audio recordings were transcribed verbatim to ensure the precision of the interviewee's responses, allowing for thematic analysis (Yin, 2017). After the file was professionally transcribed, I downloaded it to an encrypted password-protected USB drive, sent it to each participant, and provided them with a timeframe to review their transcript for correction and clarification. This process increased the dependability of the study through participant checking. The transcribed data will be kept confidential and destroyed after five years.

Data Analysis Plan

Case study data analysis examines, categorizes, tabulates, tests, and converges case study evidence to produce empirically based findings (Yin, 2017). A common problem in qualitative studies is that the data collection process results in a significant amount of unanalyzed piled-up data that needs to be analyzed by researchers (Maxwell, 2013). The research rigor is increased by interweaving the data collection and analysis processes (Miles et al., 2014). I will conduct data collection and analysis concurrently in this study according to the traditional tech case study method (Yin, 2017).

The data analysis strategy allowed me to identify emerging themes and patterns that help explain the central research question of how retail investors in US markets describe their adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor. According to Halkias and Neubert (2020), the research setting is a physical, social, and cultural site where a researcher conducts a study and studies the participants' natural settings. The focus is on meaning-making in qualitative research (Merriam & Tisdell, 2016). Documentation and understanding of the conditions under which a study occurs boost the study's replicability if another research is conducted in a similar setting. I developed codes that are grounded in the conceptual framework. I connected the result of the data analysis with the central research question and concluded so that anyone could comprehend the entire research process that led to the conclusion (Tracy, 2019).

For case study research, data analysis required a rigorous approach when applying the five analytical techniques of pattern matching, explanation building, time-series analysis, logic models, and cross-case synthesis (Yin, 2017). This study applied rigor and adopted pattern-matching logic that addressed my case study's "how." Yin's (2017) procedure for pattern matching enabled me to compare the empirically based pattern with the predicted pattern, examine the extent of the matching, offer rival explanations where necessary, and interpret and present the final study results. I predicted the study's findings by critical propositions from the literature review and my personal and professional knowledge of financial retail investors' interactions with Robo-advisors.

Thematic analysis is the primary data analysis technique used in the pattern-matching process and offers an effective and reliable data approach in a qualitative study (Yin, 2017). After each participant completed the transcript review process, I began the initial review and coding of the data by conducting two cycles of coding, the pre-codes and the actual code. Coding is a cyclical act, and it is rarely possible to arrive at perfect codes during the first cycle. The pre-coding provides the basis for coding. Once pre-coding was compared with the coding, I organized the codes into categories for thematic analysis. I classified several themes using coding categories and combined themes across my multiple data sources (see Saldana, 2016).

Yin (2017) noted that the strength of the case study researcher lies in generalizing the theoretical propositions established from the literature. Three intent-to-adopt theories frame this study: The Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model (TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) that provide a framework of theories and conceptual models by which to explain customer behavior in financial technology-based platforms and to gain a deep understanding on customer decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022). Research studies on the diffusion of financial technology and Robo-advisors to customers are predominantly grounded on these three adoption models (Atwal & Bryson, 2021). The conceptual/theoretical framework is used as a lens to explain the results of my data analysis process.

Discrepant cases are data out of congruence with the pattern or explanation emerging from the data analysis (Stake, 2010). According to Maxwell (2004), analyzing, interpreting, and reporting discrepant cases is necessary as it may help the researcher broaden, revise, or confirm the patterns emerging from the data analysis and further enhance the study’s credibility. In my data analysis results, I searched for theories, and discrepant data that run counter to themes or analyses; presenting this evidence supporting and contradicting the research’s perspectives increases the study results' trustworthiness (Maxwell, 2013).

Issues of Trustworthiness

Credibility

Establishing trustworthiness in the research method and process is essential. The author must establish believability in her/his findings by demonstrating validity and reliability criteria and that these two factors have been the standard criteria for assessing the soundness of quantitative research (Nassiji, 2020). Reliability and validity are expressed in qualitative research to address the question of audience persuasion due to the value they provide as authentic and original knowledge (Lincoln & Guba, 1985, p. 290). Lincoln and Guba highlight four trustworthiness principles, which have been accepted and considered necessary by many qualitative researchers. These include *credibility, transferability, dependability*, and *confirmability*. I rigorously followed and documented recommended and peer-reviewed research credibility processes to prove trustworthiness. Each principle and how I applied it are discussed in greater detail below.

The principle of *credibility* in qualitative research is about creating a trusted value proposition with your audience, with the original, new knowledge you have transparently created by sharing the process and the input into the final phase, which is distillation. The key to building credibility in the process is to frequent participant data capture validation, as well as triangulation with similar and other research to demonstrate the integrity of capturing unbiased data, and the citation process, which allows supporting or similar research to be brought into the research process (Nassiji, 2020). The credibility process comprises four key process demonstrations: transferability, dependability, confirmability, and ethics/ethical procedures.

Transferability

Transferability demonstrates to readers that the research findings can be applied to other similar problems and industries/topic areas and be helpful as a guide to gaining new insight. Daniel (2019) recommends a rigorous examination for clarity of description and documentation. Clarity of understanding of the research process framework to allow transferability and applicability of it to other areas/industries requires making sure the audience has a clear understanding of the problem statement, the study purpose and description, the timeline and phenomenon, the data capture approach, the participant pool demographics/characteristics, and the findings recommendation for additional areas of study and future research.

Dependability

Dependability is the qualitative research verification of applying the insights and recommendations to consistently produce stable improvements, as noted in the original research. Singh, Benmamoun, Meyr, & Arikan (2021) cite dependability process recommendations for building and documenting an audit trail so that subsequent researchers and analysts can replicate the data sources and study as needed in a related industry or topic. They also suggest adding a list of cutting-edge research articles and related work to support triangulation. Via citations and the references list, I documented the data sources used to create the research, related emergent studies in the future research recommendations section, and referenced similar studies on barriers to Robo-adoption in other countries/regions.

Confirmability

Confirmability demonstrates that the research process is free from bias/corruption and that sources, research process, and findings can be validated as having taken place in the way and the time cited in the study. Singh, Benmamoun, Meyr, & Arikan (2021) suggest that the researcher conduct a reflexive discussion of the potential biases that could be evident. I discussed the replicability integrity of the data sources, collection process, and analysis in each appropriate section. I also discussed the potential biases of each part of the study, including data collection/instrumentation and interpretation bias when developing the insights.

Ethical Procedures

In order to ensure fair, transparent, and ethical research, Walden University has a rigorous Utilization Research Review conducted by the Internal Review Board. It is the process and mechanism to oversee research quality. According to Roth and Von Unger's ethics research (2018), many essential and moral questions exist. Ethical review and reflexivity are essential to ensure the quality of every step in the research process. The researcher should challenge her/himself to make sure he/she feels the purpose is worthwhile, the audience benefits are clear, the risks to participants are mitigated and transparent, and the accountability is actionable. Asking these foundational questions should trigger some debate, as that is the purpose of the ethics review process. The fundamental principle at the core is to ask ethical questions that guide the integrity of the process and how participants will be treated during the process. It is about applying the golden rule to the research participants. Key areas and questions I examined/asked:

- Overall process ethics: IRB approval of Walden's URR application was followed closely, and each step was summarized for transparency.
- Participant selection and recruitment: I have fully outlined the participant selection reasoning and population recruitment criteria, as well as the method for selecting five to ten participants from my LinkedIn connections or groups. I reflexively reviewed the selection and recruitment results to ensure there had been no recruitment/population bias and that diverse viewpoint were represented. Since there were no incentives for participation, there was no incentive bias, but the participant pool was carefully screened for

representation bias so that friends who were recruited could provide a diverse point of view.

- Data capture: I reviewed the data collection step by step, including the instructions and questionnaire review, permission to record, instructions, as well as the statistics from the collection of data from each participant to provide transparency and oversight into the data collection and recording process. It was paramount that I reviewed the data privacy and storage process in the research section, discussed with each participant how their answers would be recorded, and made sure they understood what opting in or opting out of recording means. I reviewed and discussed for how long and where the data would be stored to be kept confidential, and overall ensured the process of protecting anonymity and privacy was discussed and understood by the participants.
- Instrumentation bias: The in-depth interview guide thoroughly discussed the rationale for construction, sequencing, and length to ensure the research goals would be achieved through the research instrument.
- Analytical approach and bias review: I discussed the data analysis approach in detail, including the data integration, the data cleaning, the data coding iterative approach, the insights distillation process, the results and conclusions deduction approach, and the examination of any possible biases in the logic used to conclude to guard against confirmation bias, halo effect bias or other possible conclusion biases.

Summary

The purpose of this qualitative, single case study with embedded units is to understand the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor. I used a single case study with an embedded unit design to address this gap within the qualitative paradigm. Understanding the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor may inform marketers to what extent American investors are willing to use Robo-advisory services instead of a human advisor to manage their retail investments.

In this discussion of the overview of the credibility process, I provided a blueprint for establishing credibility. I outlined the framework of processes that make up how credibility is established. I defined and explained why each process component was essential, providing citations and examples in other studies of how the processes were applied. I then noted how I applied each component in this study. I started with the overall principle of credibility and then explained the four components of transferability, dependability, confirmability, and ethics/ethical procedures.

I explained the rationale for the research methodology as a case study design, using in-depth interviews to isolate themes around barriers to adopting Robo-advisor use. I discussed how I established the transferability of the study results by citing other examples of similar studies and established and applied the dependability principle to demonstrate how to trace and audit the data collection and analysis findings. I gave the application approach for confirmability in the reflexive review process to examine each step to be free from bias.

The final section reviewed ethics application. I outlined how I applied the ethical principle of participant protection and data privacy protection. I discussed how each component of the research process was reflexively reviewed by myself, my committee, and the IRB through the URR process. The ethics application component discussion aimed to ensure maximum integrity of the URR process. In Chapter 4, I describe the research execution plan and framework in-depth, including demographics, data collection, data analysis, evidence of trustworthiness, and the study results.

Chapter 4: Results

The purpose of this qualitative, single case study with embedded units was to understand the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor. The topic of customer adoption of Robo-advisors remains poorly understood in the U.S. market; finance and information technology scholars wrote that there is a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). I used seven semi structured interview questions adapted from interview questions developed by Atwal and Bryson (2021) and Bhattia et al. (2021) when interviewing retail investment customers on Robo-advisor adoption in Germany and India, respectively.

The interview protocol (Appendix B) was used to collect qualitative data on understanding the adoption intentions of retail investors in U.S. markets to use a Robo-advisor. The interview protocols were both an open-access document, and the interview protocol questions were piloted and validated (Atwal & Bryson, 2021; Bhatia et al., 2021); therefore, not needing another field test conducted to test the validity of the interview questions items in the meeting the purpose of the study. When triangulated with archival data and reflective field notes, the semi structured interview data findings provided in-depth insight into participants' experiences using a Robo-advisor instead of a human advisor, the central phenomenon of the study.

Robo-advisory is at a nascent stage and is still emerging, and more information is needed to equip investors better to understand its full capability of handling different financial technology issues (Bhattia et al., 2021). Abraham et al. (2019) suggested that Robo-advisors must be designed to cater to different domestic regions of countries, an area presently under researched. My study is significant to professional practice to inform marketers when developing strategies to foster awareness and the intention to use and adopt Robo-advisors by retail investors within the United States.

This chapter describes the research setting, participant demographics, data collection procedures, data analysis procedures, and evidence of trustworthiness and presents the study results. The chapter concludes with a summary and a transition to Chapter 5.

Research Setting

Data for this single-case study were collected by conducting semi-structured interviews with seven retail investors in the United States who had experience using both a human financial advisor and a Robo-advisor. Interviews were conducted using the Zoom meeting platform and recorded on the Otter.ai application and the Google Play digital voice recorder. The interviews lasted approximately 30 minutes, in which at least 5 minutes were used to verbally review the purpose of the study and the informed consent. Participants were required to be adults over the age of 18 residing in the United States with at least 1 year of experience using a Robo-advisor for retail investing who possessed knowledge and experience using a traditional financial advisor for investing their money. The study sample's inclusion criteria replicated inclusion criteria from similar studies (e.g., Atwal & Bryson, 2021; Bhatia et al., 2021). Potential participants who did not meet the inclusion criteria were excluded from the recruitment list.

Using purposeful network and criterion sampling, participants were recruited using the LinkedIn professional social media platform. Recruitment occurred by sending potential participants requests to participate in the study via direct messaging on LinkedIn and direct email communication within the network organizations. Once connections were made, potential participants were sent the introductory letter and consent form via email. After participants responded “I consent” to my email, we coordinated a mutually agreed day and time for the interview at the candidate’s convenience.

The semi structured interview protocol (Appendix B) was created as a guideline to ensure that the interviewee was comfortable with the topic, understood the background of the research, and had some critical definitions in the context of the study area. During the interview, participants were reminded of their right to end the interview and cease participation in the study. I also reminded participants that the interview would be recorded, and I indicated to them when I started and stopped the recording. Participants appeared to be very comfortable during the interviews and expressed freely while sharing their interracial collegial relationship experiences.

Demographics

Participants for this study were selected using purposeful network and criterion sampling techniques. Purposeful sampling was used to recruit participants who could provide rich information to answer the research questions (Maxwell, 2013; Palinkas et al., 2013). The collected demographic characteristics were data points relevant to this study’s research problem and purpose of the study. The characteristics included age, gender, and opportunity to use a Robo-advisor. All participants resided in the United States.

Table 1 provides the demographic details of all participants in this study. Pseudonyms are provided in an XY format, where X is represented by the generic letter P, which stands for "participation," and Y is the unique numerical identifier assigned to each participant

Table 1

Participants' Demographics and Characteristics

Participant	Age	Gender	Education level	Years of experience using Robo advisors	Occupation
Participant 1	63	M	Associate	15	Engineer
Participant 2	65	M	Bachelor	10	Software delivery manager
Participant 3	48	F	Bachelor	20	Esthetician/business owner
Participant 4	37	F	Associate	10	Marketing and social media manager
Participant 5	73	M	Bachelor	20	Retired Merchant Marine/Boat Captain
Participant 6	19	M	Bachelor	2	Student
Participant 7	22	F	Bachelor's	4	Student

Data Collection

The data collection for this single case study with embedded units began on December 18, 2022, after receiving IRB approval from Walden University. Walden University's IRB approval number for this research is 12-14-22-0315802. The seven participants were recruited using purposeful criterion and network sampling. I sent an introductory LinkedIn message or email invitation to potential participants identified and pre-screened from the LinkedIn platform on social media. The participants were made aware of the study's aim, participation duties, and all other information that ensured they participated based on an informed decision through my initial recruitment letter (see Merriam & Tisdell, 2015).

On LinkedIn, I sent an in-platform email message to identify potential participants for this study. I sent a connection request to potential participants to be connected on LinkedIn and then followed up after connecting with a LinkedIn mail message via the platform's sharing channels. I recruited participants that responded positively to my LinkedIn message request for participation in my study. Not all potential participants to whom I sent a connection request accepted my request to connect on LinkedIn.

Once connected, I sent the introductory email and attached the consent form to prospective participants again using the LinkedIn email messaging system. I sent direct emails to those potential participants who were retail investment customers at U.S. banks. Potential participants responded with questions about the study, or the potential participant indicated that they were interested and provided consent to participate.

After identifying two to three participants who provided consent to participate in this study, I searched my own Linkedin professional network and identified potential participants who met the inclusion criteria and might be interested in participating. I sent an email and a direct message to the recommended potential participants via traditional email and LinkedIn. I sent seven invitations to participate in this study via traditional email. Overall, the feedback was positive, with seven individuals could participate. I planned to begin the interview until I reached data saturation. To the participants who accepted the invite and provided consent to participate in this study, I continued our communications via email and phone when requested to establish a date and time for the actual interview.

Semi Structured Interviews

The next phase of data collection consisted of scheduling participants for interviews. Participants were scheduled for interviews at their convenience. Interviews took place over 3 weeks, from December 18 to December 25. I used the Zoom platform to create the meeting invitation for all seven interviews, including the dial-in information, which I copied and pasted into an email invite. All interviews via Zoom were recorded via Zoom's integrated recording feature, the Otter.ai app, on my Samsung phone. I experienced no issues connecting with the experts via the Zoom platform or recording tools. The Otter.ai app automatically provided an initial transcript that was later cleaned up and corrected as needed. During the data collection process of conducting interviews, I engaged with and reviewed the checklist of possible biases concerning the participants and dismissed all biases, preconceived ideas, judgments, and concepts that I had regarding AI Robo-advisor adoption.

I also disclosed to each participant that I was a developer of AI Robo-advisor technology. I followed the semistructured interview protocol (see Appendix B) and bracketed my knowledge and experience. I listened to each participant intently and allowed participants to express themselves without interruption. I maintained a handwritten journal to complement the audit trail and balance the information across the documents. The combination of journaling and reflective notes increased the study's information and strengthened the study's trustworthiness. Participants were comfortable and expressive in their responses, and there were no signs of distress in their communication. I continued past five participants until I reached data saturation, with similar data noted from participants P5, P6, and P7 (see Schram, 2006).

Data saturation is achieved when the relative frequency of codes is stabilized, and further data points will not change the results of a study (Guest et al., 2006). No new themes emerged after interviewing eight participants, and data saturation was achieved after Participant 5. Guest et al. (2006) noted that data saturation may be attained by as little as six interviews, depending on the sample size of the population. According to Burmeister and Aitken (2012), data saturation is not about the numbers but the depth of the data. All interviews were completed and yielded rich, in-depth data from a broad spectrum of Robo-advisor users.

Member Checking

After completing each interview, I uploaded the audio file of the recorded interview to the transcription service Otter.ai for transcribing. Each transcription took between 1 and 4 hours to complete, including minor edits. Each participant was emailed a copy of the transcript for member checking to ensure the accuracy of their statements and to ensure that I had accurately captured each participant's responses. This transcript review is part of the member-checking process to ensure rigorous qualitative study results (Moser & Korstjens, 2018).

Participants were asked to respond to me within 48 hours if any edits were needed. Most participants responded beyond 48 hours. I believe that this was attributable to the busy schedules of these professionals. There were very few changes made. Two participants requested minor changes. I made the requested edits to the corresponding transcripts. Data collection concluded on December 26, 2022, after completing the member-checking process. All data collected for this study were stored in an electronic reflective journal in Microsoft Word and on a computer hard drive in mp3 format. I managed participant data confidentiality as outlined in Chapter 3.

Data Analysis

For data analysis, I used a descriptive coding strategy to assign meaning to segments of raw data collected for this study, as Saldaña (2016) recommended for novice researchers. I also tested out the new Chat GPT, and Otter.AI theme distillation capability to augment the raw data transcribed and confirmed through the member-checking process, presented a detailed understanding of the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor. Case study research involves a holistic exploration of all aspects of the case and can provide industry-related data to address a gap in the extant literature (Yin, 2017). Because the inductive approach is used in qualitative research to generate or broaden theory and allow themes to emerge from data (Saunders et al., 2018), I used the inductive approach as part of my analysis strategy so themes emerge from the raw data.

Thematic analysis is the primary data analysis technique used in Yin's (2017) pattern-matching process and offers an effective and reliable data approach in a qualitative study (Tracy, 2019). For the thematic analysis of the study, I used manual coding as recommended for early-career stage researchers. The descriptive coding method enabled me to assign meanings to raw data segments, phrases, or both for indexing and data categorization (Saldaña, 2016). I applied content analysis to the primary data. I first identified codes in the main content through in-depth interviews and then created categories from the identified codes grounded in the conceptual framework.

The next step was interpreting the data analysis, which involved comparing various themes from the data analysis generated through multiple sources (interviews, field notes, and archival data) and comparing the findings with the theoretical propositions from the literature review. Yin (2017) noted that the strength of the case study researcher lies in generalizing the theoretical propositions established in the literature. To this end, this study was framed by the following theories and conceptual models: The Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). This conceptual/theoretical framework can support the researcher in explaining and interpreting qualitative analysis results targeting customer behavior in financial technology-based platforms, gaining a deep understanding of customer decision-making, and adopting Robo-advisor services for retail investors. Research studies on the diffusion of financial technology and Robo-advisors to customers are predominantly grounded on these three adoption models (Atwal & Bryson, 2021).

Using a pattern-matching technique, I continued with the content and thematic analysis from primary and secondary data (Yin, 2017). Using the inductive analysis approach, I used the ground-up data analysis strategy (Yin, 2017) to generate codes from the transcribed data (Boyatzis, 1998). Thematic analysis is considered data-driven when the codes are generated inductively (Braun et al., 2019). Coding is a cyclical act, and it is rarely possible to arrive at perfect codes during the first cycle. The pre-coding provides the basis for coding. I also used the Chat GPT and Otter.AI text mining feature to distill themes in each transcript and across all the interviews as input into the pre-coding framework and as a stand-alone coding analysis. Once pre-coding was compared with the coding, I organized the codes into categories for thematic analysis. I classified several themes using coding categories and combined themes across my multiple data sources (see Saldana, 2016).

The next step involved interpreting data by comparing various themes from the data analysis generated through multiple sources (interviews, field notes, Chat GPT, and Otter.ai analysis and archival data) and comparing the findings with the literature review's theoretical proposition. The ability to generalize the theoretical propositions established from the literature lies in the strength of case study findings (Yin, 2017). I compared propositions within the study's theoretical/conceptual framework to the overall study findings to interpret the results and arrive at a deeper understanding of the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor.

The thematic analysis was completed using Yin's pattern-matching logic. The following three coding categories are grounded in the conceptual framework, and the nine themes emerged from data analysis of responses to the interview questions and are presented in a hierarchical list.

Coding category: Perceived risk of using of a Robo-advisor

Themes: (a) awareness of Robo-advisory systems, (b) perceptions of risk connected to customer's financial literacy, (c) data security risk lowers acceptance of Robo-advisor technology

Coding category: Perceived usefulness and acceptance of a Robo-advisor

Themes: (a) Robo-advisor is filtering out emotional customer biases, (b) customer ambivalence on Robo-advisor capabilities, (c) perceived ease of use

Coding category: Perceived adoption intentions of Robo-advisor systems

Themes: (a) Trust in the Robo-advisor**,** (b) customer ambivalence on adoption intention, (c) low adoption intention for customers with low financial literacy

Figure 2 below visually represents aligning the study's problem, RQ, and conceptual framework as the foundational elements from which codes and themes derived from interview data exploring the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor.

Figure 2

Codes and themes alignment with the study's foundational elements

Problem Statement:

While banks are set to invest heavily in developing AI value-driven competencies, the successful adoption of Robo-advisors within the financial services industry will depend on gaining a critical understanding of the customer's potential barriers to AI adoption (Atwal & Bryson, 2021; Tsai & Chen, 2022).

Central Research Question:

How do retail investors in US markets describe their adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor?

Conceptual Framework:

Concept of "(TPB) Theory of Planned Behavior".

Author: Ajuzen

year: 1991.

The Theory of Planned Behavior (TPB) was developed by Ajzen (1991) as a prediction tool for intention to behave in a specific manner, assessing attitudes toward the behavior, subjective norms, and perceptions of being in control. In TPB, individual social aims are planned by disposition, abstract standards, and conduct control.

TPB has been used to explain and predict behavior across various behavioral domains, including technology adoption (Ajzen, 2020). An extension of TPB was developed by Davis (1985) and named the "Technology Acceptance Model" (TAM). Davis et al. (1989) wrote that TAM could explain that users' intention to use an information system is determined by perceived use, usefulness, and attitude toward use.

Davis adopted the theoretical views of Ajzen and Fishbein's (1975) theory of reasoned action (TRA) to show the perceived usefulness and ease of use.

Conceptual Framework:

Concept of "TAM: Technology Acceptance Model ".

author: Davis

year: 1985.

An extension of TPB was developed by Davis (1985) and named the "Technology Acceptance Model" (TAM).

Davis et al. (1989) wrote that TAM could explain that users' intention to use an information system is determined by perceived use, usefulness, and attitude toward use.

Davis adopted the theoretical views of Ajzen and Fishbein's (1975) theory of reasoned action (TRA) to show the perceived usefulness and ease of use.

Conceptual Framework:

Concept of "Unified Theory of Acceptance and Use of Technology".

author: Venkatesh

year: 2003.

The "Unified Theory of Acceptance and Use of Technology" (UTAUT) was proposed by Venkatesh et al. (2003), which replaced the attitude construct in TPB and iterations of TAM and developed their theory using new constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions as critical predictors in the adoption of technology.

Research investigating investors' adoption of Robo-advisory services remains limited, perhaps because of its recent market introduction (Tsai & Chen, 2022).

Further elaboration on the logical connections among critical elements of the framework to the study's purpose and its relation to the study approach, research questions, and research method is further explained in Chapter 2.

Finance and information technology scholars wrote that there is a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). Many studies on Robo-advisor adoption have been conducted in Asia; thus, more studies are needed to explore precursors of Robo-advisor adoption within Western financial market contexts to recommend future quantitative studies that will provide some generalizable findings (Atwal & Bryson, 2020; Gan et al. (2021). Answering the study's research question contributes original, qualitative data to the management and finance body of literature by extending the three adoption models explaining the diffusion of financial technology and Robo-advisors to customers for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022).

Evidence of Trustworthiness

Credibility

The principle of *credibility* in qualitative research is about creating a trusted value proposition with your audience, with the original, new knowledge you have transparently created by sharing the process and the input into the final phase, which is distillation. I worked on participant data capture validation and triangulation with similar and other research to strengthen the credibility of capturing unbiased data and the citation process, which allows supporting or similar research to be brought into the research process (Nassiji, 2020). I worked on ensuring the credibility of the study results by evaluating whether the research findings represent a convincing conceptual presentation of the data (Korstjens & Moser, 2018). I aimed for reliable study results following the method and procedure recommended by seminal case study methods scholars (Stake, 2013; Yin, 2017).

Transferability

Transferability demonstrates to readers that the research findings can be applied to other similar problems and industries/topic areas and be helpful as a guide to gaining new insight. As Daniel (2019) recommended, I ensured that my research's foundational elements were written to be comprehensible to the target reading audience. Having passed reviews by my Dissertation Committee, I felt confident that my reading audience had a clear understanding. In achieving transferability, fI detailed a thick description of the context, the setting, and the method adopted for the research in the research design to help any researcher seeking to replicate this study within a different context in the future to make a reasonable judgment that will aid and ease the transferability (Morse, 2015). The interview questions were generated from the literature that conceptually and theoretically grounded this the study

Dependability

Dependability is the qualitative research verification of applying the insights and recommendations to consistently produce stable improvements, as noted in the original research. I developed a clear audit trail so that subsequent researchers and analysts could replicate the data sources and study as needed in a related industry or topic. I correctly documented the data sources to develop the stud's problem, purpose, and research question. My future research recommendations section referenced similar studies on barriers to Robo-adoption in other countries/regions. The interview protocol (Appendix

B) was used to collect qualitative data on understanding the adoption intentions of retail investors in US markets to use a Robo-advisor. The interview protocols were both an open-access document, and the interview protocol questions were piloted and validated (Atwal & Bryson, 2021; Bhatia et al., 2021).

Confirmability

Confirmability demonstrates that the research process is free from bias/corruption and that sources, research process, and findings can be validated as having taken place in the way and the time cited in the study. I discussed the replicability integrity of the data sources, collection process, and analysis in each appropriate section. My Dissertation Chair and I continuously communicated on mitigating potential biases during data collection/instrumentation and interpretation of the study results. I kept reflective field notes throughout the study, recording and reviewing my observations and interpretations to strengthen the study's confirmability (Morse, 2015).

Study Results

I developed the research question for this study based on the purpose of the study, the research problem, and the qualitative research design. The purpose of this qualitative, single case study with embedded units was to understand the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor. The topic of customer adoption of Robo-advisors remains poorly understood in the US market; finance and information technology scholars wrote that there is a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). The central research question for this transcendental, phenomenological study was: *How do retail investors in US markets describe their adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor?*

The interview questions reflected the various perceptions and challenged US retail investment customers faced in adopting Robo-advisor technology. The interview guide for this study (Appendix B) consisted of semi-structured questions adopted from interview questions developed by Atwal and Bryson (2021) and Bhattia et al. (2021) when interviewing retail investment customers on Robo-advisor adoption in Germany and India, respectively. My study filled the literature gap in the lack of understanding of US customer adoption intentions of Robo-advisor technology, and participants' responses were categorized into the following nine themes based on the coding and thematic analysis results.

Awareness of Robo-Advisory Systems

This theme refers to the general widespread awareness of and familiarity with what Robo-advisor technology is and its essential capability on a surface level across a spectrum of ages, genders, and varying levels of education and socioeconomic status. Research has shown that barriers to entry are significantly reduced or non-existent with the Robo-advisor platform, allowing more providers aligned to niche and specific target markets to provide different combinations of Robo-advisory services and address different needs within target markets, including generational interaction requirements (Cheng, 2022). Participants discussed their awareness and familiarity with Robo-advisors and how long they have been aware and familiar with them across multiple platforms.

Participant 2:

"I'm familiar, but not an expert at using them."

Participant 3:

"Very familiar with it."

Participant 5:

"I'm very familiar with doing online banking and investing. I don't know how much really I've used advisement services in that area. I mean, basically, you know, what I do is, I mean I see this information and then if it looks interesting, I'll do some more research. Okay, yeah. And that's, that's what we mean. So you're fairly familiar you would say right, yeah."

Perceptions of Risk Connected to Customer's Financial Literacy

This theme refers to customers' perceived risk of using a Robo-advisor and how they believe it may manage risk. Customer perceptions may differ on risk perceptions depending on their business and academic education and financial management literacy. The research According to Piehlmaier (2022), the age factor is the single and most significant adoption driver for Robo-advisors. Reading deeper into the analysis, the real driver is the desire to make money because one has his/her whole life ahead to recoup any losses and is not as afraid of risk-taking. This is where the overconfidence driving the adoption of rob-advisors comes in.

The quantitative analysis of 2,000 investors who completed an investment behavior and satisfaction survey was analyzed. The findings from a generalized linear model show that increased financial knowledge and literacy decrease the likelihood of adopting a Robo-advisor. However, in a contradictory finding, the model findings also support that increased financial risk-taking is associated with using a Robo-advisor, as is having strong confidence in one's financial knowledge. Oehler et al. (2021) paint a similar portrait of financial savvy guiding the precise use of Robo-advisors for stock and bond investing but highlight the trust and human connection/friendship with an advisor as a specific obstacle to using a Robo-advisor. The participants discussed their confidence in using Robo-advisors and their perceptions of risk of use and risk management ability, given their financial literacy.

Participant 1

"Well, since I don't use it, I can't really answer this question. In terms of effectively estimating your level just like oh even social media databases and everything. They can they can do a biased algorithm and sell one product or one service or one stock over another based on not even any facts or data based on the commercial viability of it. So there's just, you know, it's like a Google search that you pay to have your company show up first. So I have no trust no faith."

Participant 2:

"Oh, yeah, I feel that given the correct amount of instructions that they may be even better at defining risk, because they're just looking at it as your quantitative measure versus someone else's opinion of what a certain level is."

Participant 3:

"I think that a lot of time and thought and money goes into them being able to predict and assist you with different kinds of things. So I think they are. I think they're pretty accurate. If you're giving them the accurate information. I think the outcome is pretty accurate."

Data Security Risk Lowers Acceptance of Robo-Advisor Technology

This theme refers to how the customer perceives the likelihood of data security risk and faith in the ability of machines and the banking institution to safeguard their information and how a low level of trust in data security and accuracy lowers the acceptance and adoption of Robo advisor technology. The research found that since Robo-advisors are disruptive change agents and new technology, there are varying degrees of exposure, experience, and willingness to adopt Robo-advisors (Guo, 2020).

The study, therefore, highlights a gap in the research and the need for segmented Robo-advisor adoption research by traditional demographics such as age, gender, race, experience, exposure, and willingness to use Robo-advisors and technology in general. The study also touches on the need to understand social media and other contextual societal influence factors, including ethical and legal factors such as availability/accessibility and socio-economic barriers, presumably also by those same experiences, exposure, and willingness to use Robo-advisors (Belanche et al., 2019). Participants discuss their ambivalent views of banks' and machines' abilities to protect their data and manage data security. Customers have varying confidence levels with banks/financial institutions and their ability to trust that their data will be secure. When the customer feels a high data security risk, they are far less likely to be open to continuing and considering increasing the adoption of Robo-advisors.

Participant 1:

"The computer world isn't perfect. It's the Wild West and terrifies me. The data is never secure. I'm not, it doesn't matter what everyone tells you. Your data is not secure. And it just takes one hack. And it's over. And it's that simple. It's just that simple. When something has me typing my social security number I get all worried initially as I don't have any trust in AI and data security."

Participant 2:

"As compared to having a human responsible, I believe that computers, or robos have the ability of being hacked into is just a matter of staying ahead of the hacker. And I understand that because I am in the industry."

Participant 3:

"I'm pretty confident. I mean, I know that there's been leaks and there's always like, something but it's never going to be perfect. So a fairly strong level of confidence."

Robo-Advisor is Filtering Out Emotional Customer Biases

This theme addresses most participants' views that customers perceive a Robo advisor, because of its algorithmic, rule-based, objective nature, as a favorable tool to detect biased, possibly risky financial decision-making. The research supports the fact that for retail investors, the Robo-advisor has gained considerable attention in financial decision-making and has emerged as an effective alternative to traditional financial advisors with benefits including lower charged fees, ease of use, and diversified services (Bhatia et al., 2020; Brenner & Meyll, 2020). The study participants discussed their mixed views on robo-advisors' ability to address behavioral biases, with most favoring the use of robo-advisors as a guide to detecting possible patterns of bias that could be considered.

Participant 4:

"Hmm. That's a tough one. I guess I would be a little more confident in that one, maybe. Just from the aspect of it, that you're able to see things that you're interested in and then maybe I can pull different statistics or you know, risk factors and you know, what other you know, competition or things through people who have done similar things, maybe pull that information and compare so maybe that one I would have a little more confidence in how we interface to think but but, yeah, okay, but yeah, that I see you'd have a little more confidence to detect risk. It thinks that might be too risky for you, even though there might be ads to invest in that FTX which, so many people do, but you know, a lot of people didn't have the tolerance for it."

Participant 5:

"I guess if you had all the information, you know, I'd have some a little confidence. I think it's just about every interaction with a portal is driven by some kind of recommendation or rule or some, some suggestion."

Participant 7:

"Yeah, I think they have a very good ability to deal with data and I think definitely on the production side of things, and they're dealing with big data that behind the scenes now, so I am talking in the middle. However, I think there are some things you know, that might not be accounted for but these you know, different disasters and things that might you might run into a point in time, that are kind of those outstanding circumstances that a guy does not, you know, counselor that a human might kind of think about"

Customer Ambivalence on Robo-Advisor Capabilities

This theme refers to how effective and valuable customers perceive Robo-advisor capabilities to be. There was a mixture of positive and negative views from most participants, and no participants felt highly confident that Robo advisors were completely effective as they are. The participants felt ambivalent because their experiences were not always helpful or easy. The research supports that customer value delivery appears to be at a low level in banks, and their services are not enough for the customer, who only sees banks as not meeting the holistic value required from the customer's point of view (Scholz, 2021). In customer-focused front-office applications, the bank customer will play a crucial role in the adoption intention of Robo-advisors (Greve & Meyer, 2021Participants observed:

Participant 3:
"I'm of two minds. I think that it's probably very accurate if you give it accurate information. But I would never invest without a human touch in anything. So not really. I am not terribly confident and would never do it without the sort of double final guidance of a banker advisor. Yes, I think that you know, anything automated and, like anything robotic, is great for initial findings and to help to help the person that's going to help you and speak with you kind of guide them a little bit and gather information so that they can help you better but not to go through the entire process this anything automated from A to Z."

Participant 4:

“Hmm. That's a tough one. I guess I would be a little more confident in that one, maybe. Just from the aspect of it, that you're able to see things that you're interested in and then maybe I can pull different statistics or you know, risk factors and you know, what other you know, competition or things through people who have done similar things, maybe pull that information and compare so maybe that one I would have a little more confidence in how we interface.”

Perceived Ease of Use

This theme refers to how easy to use the customer/participant felt the Robo advisory services were or were not. Most participants/customers had both good and challenging experiences with ease of use, with one participant encountering a significant processing error creating both a technical and trust ease-of-use barrier that he refused to work through. The research supports that ease of access to receive advice is a primary motivation to consider using a Robo advisor and is a deterrent if not perceived as easy to use by each customer. Advice-seeking retirement portfolio investment management is only weakly correlated with market returns, clouding the value proposition case for personalized investment advice and one of Robo-advisors' primary value drivers (David & Sade, 2019). The participants had fairly positive perceptions on the ease of use:

Participant 5:

“I say yes, because I really haven't had great experiences with human financial advisors. Could you elaborate on that experiences a little bit if you're comfortable at all, not now. Don't feel like you have to talk about anything. You don't want to like what kinds of not great experience? Okay. In one case, the advisor really offered no advice other than feeling like one of those eight asset allocation, mutual funds and that that was the extent of his ability to advise another one turned it all over to his company's kind of cookie cutter, cookie cutter portfolio. turned out not to be a great investment. A third one has been open and honest. I think what is your advice but the products offered some was really bad. So that's been my experience. While there was another one who tried to do some double talk about how the market goes up longer than it goes down and wanted, like 2% of my investment says, Listen, I really wasn't saying what he was going to do with it. So three out of four, you know, we're not really helpful."

Participant 6:

"The answer is yes. So that you see it as cost effective. As an alternative to talking to a human. I think the desire and trust level will vary depending on what's happening in the market. But honestly, generally, I would trust the robo advisor as much as the human advisor. I have a strong degree of trust in what is being built."

Participant 7:

"I haven't faced myself limits of trust. Because I feel like you know, they can be in understand accepting circumstances and other things that might be influencing my decisions to say such as best. I do, however, think that considering that the bigger the other side of the coin as they might have, you know, a lot of analysts and being able to really like dive to the data on each other and collect trends that I may not recognize myself."

Trust in the Robo-Advisor

This theme centers on the participants'/customers' trust in the Robo advisor- both the institution and the technology and customer experience it delivers. The trust in Robo-advisors spanned the spectrum from one participant who expressed complete distrust in both the Robo advisor and the investment bank due to an ongoing significant administrative error, to a relatively confident sense of trust in using Robo-advisors due to increased financial and technological literacy and familiarity. Participants observed that:

Participant 1:

"I refuse to use it, due to lack of trust. The bank screwed up my allocation of my 401K funds, they labeled my contributions as the company contributions, which caused me tremendous aggravation to try to correct. I have experience with exposure to them but I refuse to use their robo advisory services due to that lack of trust issue caused by their error. No, I would not trust a robo-advisor at all. It's not personal. It's an impersonal relationship. It's you're just plugging yourself into a square peg round hole and it just doesn't. It's just wrong. If it's my finances, my finances are very personal to me. And I think the company that wants my business should make it personal to them".

Participant 2:

"Personally, I do not trust the digital advisor because of the lack ability to ask detailed questions that may or may not be a black and white may not be looking for a black and white answer, or a yes or no answer. When you're asking a question that's made possibly a great response. The robo type of advisor is less beneficial".

Participant 6:

“The answer is yes. So that you see it as cost effective. As an alternative to talking to a human. I think the desire and trust level will vary depending on what's happening in the market. But honestly, generally, I would trust the robo advisor as much as the human advisor. I have a strong degree of trust in what is being built”.

Participant 7:

“I haven't faced myself limits of trust. Because I feel like you know, they can be in understand accepting circumstances and other things that might be influencing my decisions to say such as best. I do, however, think that considering that the bigger the other side of the coin as they might have, you know, a lot of analysts and being able to really like dive to the data on each other and collect trends that I may not recognize myself.”

Customer Ambivalence on Adoption Intention

This theme describes the overall conflicting and sometimes tepid or vehement opposition to the Robo-advisor adoption intention. There are varying adoption intentions based on the participant’s financial and technical literacy level, education level, and previous banking and Robo advisor experience. Those who were financially and/or technically literate and had good or neutral previous experiences using a Robo-advisor were more likely to have more intention to at least consider continuing to use a Robo-advisor. The research supports that Piehlmaier (2022) also suggested that the persona of someone most likely to adopt a Robo-advisor is a young person (under 40) who is egotistical, greedy, and anxious to make money as quickly as possible, and has not experienced the painful consequences of a significant financial loss made from a quickly made decision. Participants/customers observed their intention to adopt.

Participant 2:

"My thoughts are that the more experience using them and beneficial experiences using them will drive people to continue to expand because overall, I think it is a good idea because you're taking the personal benefit of like if a person is doing something, an advisor may have an alternative agenda. I want person to buy stock, because I'm going to gain the most profit or I'm going to get the most I'm going to make the most money out of making that sale. Versus a computer unless you program it a certain way is only going to give you the facts. The computer doesn't care if you make money or lose money. They're just giving you the data. There is modeling. From that standpoint, your robo advisor is going to give you a more honest advice based upon the fact that you are the data you have provided. So in my opinion, that that's a good thing. And the more confident you get in using that, the more people are gonna get more used to it and use it, versus today they may they hear a robo response and ask do I feel comfortable talking to a non person about this? So in my case, I'm probably not completely beyond that. That role yet. But I think in a year to the next five years, the trade off there's a kind of a trade off or a balance between the objectivity and lack of lack of self agenda or self dealing or opportunity, versus the con of feeling like there's not the ability of the machine there's not the ability to distinguish some of the finer points of your needs. So, as you see those proof points, starting to play out, that would help you to kind of move towards greater adoption."

Participant 3:

“I would continue online banking and things like that. More specific to suggestions during online banking I never take any of those invitations that I see. If this is something that I'm interested in I pick up the phone and call to speak to somebody. I have the intention to consider the advice but I don't act on it unless it is validated by a human. So I wouldn't act fully on it, but I have the attention to keep considering, at least thinking about what comes my way through these robo advisor suggestions. But I just have no intention to act on it without a human.”

Low Adoption Intention for Customers With Low Financial Literacy

This theme refers to how the participants/customers who are not financially literate/comfortable working with banking are much more suspicious/distrustful and have a lower intention to adopt Robo advisors in the future.   The research that Fisch et al. (2017) completed supports this. It chronicles the emergence of the human vs. pure Robo-advisors and the hybrid combination following each delivery type in their research. The pure Robo-advisor is the single interface between the customer and the client. These pure Robo-advisors work well with digital/remote banks and other financial institutions with clients who do not need or want human interaction. These customers tend to come from younger demographics, such as Gen Z and Gen Y, as they have been raised as digital natives and are very comfortable navigating financial applications and managing their money and assets digitally (Dagar et al., 2020).   The contrast of the non-financially savvy over 40 versus the under 40 digital natives that are financially literate as participants/customers gave the following feedback:

Participant 1:

"No way in hell. These things all look good from some point in an organization for management decisions and organizations that run these banks. Yes, I get it. They're running a business. But I'm not going to engage unless you answer the phone and if you hire the right people, maybe I'll trust them."

Participant 4:

"I feel like that's just the way the world's going is with those types of interfaces and technology. So I mean, I will continue to interact with them. I'm hoping like the technologies get better and they're not so broad range and it's kind of more fine tuned to, you know, the situation that you know, me specifically whoever would need but I mean, I feel like that's just where the world's going less people are going to be your it's harder to get somebody on the other line. So, you know, I definitely will use it frequently. I intend to keep using them. And yes, your comfort level is such that and you you see the growth, the trajectory, so you're really comfortable with continuing to use them and grow, grow to use. Absolutely."

Participant 6:

"I will continue using it as needed either state before I use it in an extended capacity. As the years go on, and the technology gets better, hopefully be a lot more positive experiences than they were back then. So, you're going to watch and see how it progresses. And you know, see and moderate your use accordingly. Especially with key features or updates, major updates and see how that would affect you. So you intended to use that and as things progressed, but you're proceeding cautiously and we'll watch Robo advisors."

Participant 7:

"I would continue to use them to monitor my investment. You know, small pieces of advice, but personally but not some bigger decisions. Maybe. I'll probably engage the Robo advisory testing still on the big pieces then make sure I can double check that and go to human advisor. So you want to continue to use them to be cautious about the size. Impact the decision where you use them or use them as an initial interactive research guide."

Summary

In this chapter, I described the research setting, participant demographics, data collection procedures, data analysis procedures, evidence of trustworthiness, and the study results. I presented the result of the thematic analysis of nine participants, followed by synthesizing the results to this study's central research question: *How do retail investors in US markets describe their adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor?* Three conceptual categories with nine themes emerged from the findings of this single case study with embedded units. The Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) provided a framework of theories and conceptual models I used to interpret and explain customer behavior in financial technology-based platforms.

The thematic analysis provided rich data on the experiences of participants. The three codes that emerged are as follows: (a) perceived risk of using of a Robo-advisor, (b) perceived usefulness and acceptance of a Robo-advisor, and, (c) perceived adoption intentions of Robo-advisor systems. The nine themes that emerged from the data analysis process include the following: (a) awareness of Robo-advisory systems, (b) perceptions of risk connected to customer’s financial literacy, (c) data security risk lowers acceptance of Robo-advisor technology, (d) Robo-advisor is filtering out emotional customer biases, (e) customer ambivalence on Robo-advisor capabilities, (f) perceived ease of use, (g) trust in the Robo-advisor, (h) customer ambivalence on adoption intention, (i) low adoption intention for customers with low financial literacy.

I demonstrated the study’s trustworthiness using methods established by seminal qualitative methodology scholars (see Lincoln & Guba, 1985; Stake, 2010; Yin, 2017). Chapter 5 will present the finding's interpretations and I will present in what ways the study findings confirm, disconfirm, or extend knowledge in the discipline by comparing them with the peer-reviewed literature described in Chapter 2. Finally, I will present the study’s limitations and implications for social change, theory, and policy and recommend further research. And a conclusion to the study.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this qualitative, single case study with embedded units was to understand the adoption intentions of retail investors in U.S. markets to use a Robo-advisor instead of a human advisor. The topic of customer adoption of Robo-advisors remains poorly understood in the U.S. market, and my study addressed a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). To reach answers to the study's central research question, I used qualitative data collected from multiple sources of evidence, including interviews, field notes, and archival data (Merriam & Tisdell, 2015). I used data triangulation to establish the data analysis's trustworthiness (Guion et al., 2011). I used qualitative research methods to gather data that reflected the participants' perceptions of customer adoption of Robo-advisors. Qualitative interviews allow the researcher to elaborate further with the participants so that unexpected or divergent data may emerge (Halkias & Neubert, 2020; Stake, 2010).

Using a qualitative single case study with an embedded units approach allowed me to give voice to U.S. retail and investment customers on the specific nature of Robo-advisor adoption. The Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) provided a framework of theories and conceptual models I used to interpret and explain customer behavior and experiences in financial technology-based platforms and to gain a deep understanding on customer decision-making and adoption of Robo-advisor services for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022). Research studies on the diffusion of financial technology and Robo-advisors to customers are predominantly grounded on these three adoption models (Atwal & Bryson, 2021). Using a single case study with embedded units design was beneficial in this study because it gave me the flexibility to contribute original qualitative data to theoretical models of technology adoption (Halkias & Neubert, 2020; Stake, 2006). New knowledge emerges from recognizing patterns in the collected data and the logical arguments that underpin them (Eisenhardt & Graebner, 2007).

After each participant completed the transcript review process, I began the initial review and coding of the data by conducting two cycles of coding, the pre-codes and the actual code. The pre-coding provided the basis for coding. Once pre-coding was compared with the coding, I organized the codes into categories for thematic analysis. I classified several themes using coding categories and combined themes across my multiple data sources (see Saldana, 2016). The thematic analysis completed using Yin's (2017) pattern-matching on primary data from face-to-face interviews with seven participants revealed the following nine themes: (a) awareness of Robo-advisory systems, (b) perceptions of risk connected to customer's financial literacy, (c) data security risk lowers acceptance of Robo-advisor technology, (d) Robo-advisor is filtering out emotional customer biases, (e) customer ambivalence on Robo-advisor capabilities, (f) perceived ease of use, (g) trust in the Robo-advisor, (h) customer ambivalence on adoption intention, and (i) low adoption intention for customers with low financial literacy.

Interpretation of Findings

The findings of this single case study with embedded units confirmed or extended current knowledge in the technology adoption and finance literature, with each case producing data aligned with foundational theories that ground my study's literature review. In this section, I present and review the study's findings in the context of the three coding categories that emerged from the thematic analysis: (a) perceived risk of using of a Robo-advisor, (b) perceived usefulness and acceptance of a Robo-advisor, and (c) perceived adoption intentions of Robo-advisor systems. I compare these three categories with relevant concepts from the conceptual framework and the extant literature presented in Chapter 2.

I also provide evidence from the seven semistructured interviews to support how the study's findings confirm, disconfirm, or extend existing knowledge. This process of analyzing and presenting data evidence for theory extension in a single case study design demonstrates the complexity of using qualitative data's inductive and deductive evaluation processes (Halkias & Neubert, 2020). Extension studies, such as this single case study with embedded units, provide replication evidence and support the extension of prior research results by offering new insights and possible directions for future research (Bonett, 2012).

Perceived Risk of Using of a Robo-Advisor

The social problem is that while using Robo-advisors in financial institutions has become a popular trend, early adopters' socio-psychological barriers may thwart the long-term success of this AI application to long-term use (Merkle, 2020; Tsai & Chen, 2022). Traditional financial advisors help the customer by assessing their needs and objectives, defining their level of risk, and investing their customers' money according to this risk (Scholz, 2021). For retail investors, the Robo-advisor has gained considerable attention and has become a growing trend to outnumber traditional financial advisors with benefits due to lower charged fees, ease of use, and diversified services (Bhatia et al., 2020; Brenner & Meyll, 2020).

My study confirmed that all the participants had some risk aversion to using a Robo advisor, with their perceived risk level varying based on their past in-person and digital experiences, their level of financial and technological literacy, savviness/comfort, frequency of use, age, and overall socio-economic status. These results aligned with Piehlmaier's (2022) research, which showed that although the age factor is the single and most significant adoption driver for Robo-advisors, the real driver is the desire to make money because one has his/her whole life ahead to recoup any losses and is not as afraid of risk-taking.

The study findings support that increased financial risk-taking is associated with using a Robo-advisor, as is having strong confidence in one's financial knowledge. Oehler et al. (2021) painted a similar portrait of financial savvy guiding the precise use of Robo-advisors for stock and bond investing but highlight the trust and human connection/friendship with an advisor as a specific obstacle to using a Robo-advisor. This study adds and extends the theory that lack of poor experience with the financial institution (whether because of youthful inexperience or fortune not to have had poor customer experience throughout the relationship online or offline), as well as financial and overall confidence and literacy, hasten the adoption and lessen the anxiety connected to the risk-taking that using a Robo advisor is perceived to bring. All participants said their willingness to risk using a Robo advisor was governed by a sense of caution. Participants preferred to test smaller transactions and investment recommendations and expand their use based on their previous and their satisfaction with the most recent experience, as well as their level of risk tolerance.

Perceived Usefulness and Acceptance of a Robo-Advisor

Davis' (1985) extension of the Theory of Planned Behavior became the "Technology Acceptance Model" (TAM). Davis et al. (1989) hypothesized that TAM could explain that users' intention to use an information system is determined by perceived use, usefulness, and attitude toward use. Although TAM has shortcomings in omitting risk perception, the theory is one of the most widely adopted conceptual models in studying technology acceptance. Since Robo-advisors are disruptive change agents and new technology, there are varying degrees of exposure, experience, and willingness to adopt Robo-advisors (Guo, 2020).

The study addresses a gap in the research and the need for segmented Robo-advisor adoption research by traditional demographics such as age, gender, race, experience, exposure, and willingness to use Robo-advisors and technology in general.

My research findings support a general requirement across users that the technology is straightforward in what it was recommending and why to create a basic level of comfort to engage. All the participants expressed an explicit requirement that the Robo advisor interface be simple, clear, and straightforward to interact with and that the algorithms, rules, and recommendations be transparent and logical to understand. The one participant that had a horrible banking error made that created anything but transparency and ease of use refused to consider using a Robo advisor.

Perceived Adoption Intentions of Robo-Advisor Systems

The specific management problem is that little is known about the adoption intentions of retail investors across Western financial markets to use a Robo-advisor instead of a human advisor (Hentzen et al.,2022; Piehlmaier, 2022). Traditional financial advisors face challenges brought about by the increasing presence of Robo-advisor-based services (Fisch et al., 2019). Successful traditional client-facing financial advisors develop deep relationships with clients over time, invest more time in providing services, and use quality administrative and executive support to manage and operate their advisory firms (Fan & Chatterjee, 2020). For retail investors, the Robo-advisor has gained considerable attention in financial decision-making and has emerged as an effective alternative to traditional financial advisors with benefits including lower charged fees, ease of use, and diversified services (Bhatia et al., 2020; Brenner & Meyll, 2020).

My study results provide new, solid adoption insights into U.S. customers' intentions and describe barriers and facilitation recommendations. Participants expressed varying adoption intentions governed by their previous banking relationship experience, financial and technical literacy, confidence, frequency of use, age, and socioeconomic status. All participants in the study were aware of and had exposure to Robo-advisors, and all but one intended to adopt Robo-advisors with greater frequency in the future as long as the ease of use and transparency of function were apparent to them.   Every participant in the study also expressed the importance of continuing to earn their trust by protecting their data through secure platforms and processes, as well as being able to customize the Robo advisor value proposition- services, products, offers, to their needs based on their relationship with the financial institution.

Limitations of the Study

Limitations are influences the researcher could not control, shortcomings in the design, study conditions, or restrictions on their methodology affecting results and conclusions (Tracy, 2019). When conducting research, scholars must be well-versed in the limitations of the selected study design, data collection, and analysis methodology to ensure valid and reliable results. The researcher’s method and personal bias related to the circumstances and the environment were inherent limitations of qualitative research. This study faced limitations in capturing the up-to-the-minute adoption intentions for the fast-moving space of evolving Robo-advisors across the wide-ranging financial services industry. Specific factors within the study design may also pose limitations (Merriam & Grenier, 2019).

Study participants were purposefully selected; I planned to use snowball sampling if the sample size was not initially attained (see Yin, 2017). It was recognized that a small sample size might not represent the larger population of Robo-advisors usage intention challenges. This limitation was mitigated by providing a detailed audit trail and triangulation of interview responses, historical literature, and field notes to collect accurate data to answer the research question (Halkias & Neubert, 2020).

Purposeful and snowball sampling was used to achieve the minimum number of appropriate participants preferred by scholars to provide an information-rich body of in-depth material pertinent to the study (Eriksson & Kovalainen, 2015). When evaluating qualitative research with small sample sizes, distinct environments, and unique experiences, the findings and conclusions may not directly apply to other studies and populations. A study's limitations are characterized by factors in the design or methodology that impact or misinterpret the research results. The researcher's method and personal bias related to the circumstances and the environment were inherent limitations of qualitative research. In this study, specific factors may have also posed limitations. When evaluating qualitative research with small sample sizes, distinct environments, and unique experiences, the findings and conclusions may not have directly applied to other studies and populations (Stake, 2010).

Several key limitations of the study needed to be overcome or mitigated. The first was the sampling approach to ensure diversity of experiences, thoughts, and opinions. I used the combination of the purposeful and snowball sampling approach to ensure that I recruited diverse participants in age, gender, occupation, and socioeconomic status. That limitation was well addressed as the study contained seven participants ranging from 19 to 73 years old, four men and three women, four college-educated and three non-college-educated participants, with occupations ranging from college students to marketing managers to computer software engineers to retirees. The question/instrument interpretation was controlled by using the same script and reviewing the same definitions of key terms to ensure consistency of key term definition. The survey was not started until these terms were reviewed and clearly understood, and any questions from the participants were addressed.

The accurate capturing of the responses was accomplished by, with each participant's permission, a simultaneous AI-driven instant transcription app to allow the interviewer to see the answers being transcribed and follow up on adequately capturing the proper phrasing. Each participant was minimally guided and prompted to answer interview questions by the interviewer and allowed to say anything they chose as a response and to ask any questions as follow-ups. The interviews all lasted roughly 20 minutes, so there was no response bias to capture significantly more input from some participants than others.

The interviewer's role was kept to a minimum by asking the initial questions and clarifying some participants' answers to ensure the true meaning of the participant's answers was understood. Member checking was also followed, with transcripts of the interviews sent to participants for their review and correction if needed. The theme coding and distillation were approached by human qualitative interpretation, coding methodology, and Chat GPT testing for comparison. The theme distillation was consistent with all three methods, indicating that the interpretation bias was addressed sufficiently and that consistent main idea themes were developed.

Recommendations

Recommendations for Professional Practice

Research indicates that Robo-advisors are cost-effective as compared to human financial planners. From my results and other similar research, samples of populations in replicated results show that Robo-advisors primarily fulfill sophisticated investors’ needs. Customers’ exposure to adverse experiences and the need for financial services, including confidence in investment decisions, are factors that both attract and detract from Robo-advisory services. Participants who identified as retail investors were frightened by the idea of a virus attack on the Robo-advisor system and manipulation of their personal data by third-party sources. Participants that rejected Robo- advisor services believe that the AI in the banking system is not yet sophisticated or secure enough to protect their investments through Robo-advisory systems. All the issues mentioned above are ones that banks and finance company experts need to address to expand Robo-advisor services across national populations.

It is easy to note that the essential aspects of risk profiling are the socioeconomic variables that elicit the investors' behavior. A better understanding of behavioral finance, specifically the risk tolerance perspective, can help investors understand Robo-advisor investment strategies. Undoubtedly, the customers' financial literacy plays a role in adopting Robo-advisor services. Nevertheless, this points to a broader issue of embedding financial literacy education early in the school system, in much the same way technology education now begins in elementary school. The training and education initiatives of countries where Robo-advisors are used widely need to be investigated for their efficacy. Formal training in financial literacy within the American school systems can be expanded past the classroom and through social media sites such as Instagram nd TikTok favored by younger populations.

Information about investing and financial technology, including platforms such as Robo-advisory, should be included in the college curriculum. Fintech firms, maybe in collaboration with educational institutes, should undertake an initiative to develop applications for mock trading, so younger users better understand using Robo-advisor services. On the other hand, banks are one of the prominent institutes which have interaction, either physical or digital, with investors and potential investors. Thus banks should be used as a reference point to disseminate information and increase public awareness of robo-advsior services.

Recommendations for Scholarly Research

Now that this research has qualitatively established key adoption intention themes for US investors/customers of retail financial institutions, the next logical step is to conduct quantitative research to validate the critical adoption themes to ensure they are generalizable and how they vary by key demographic and needs segments. Given that targeting and personalization are key findings, the quantitative research should also be robust enough to create those critical theme alignments by demographic and needs segment. This research is preliminary in nature and can serve as an adequate foundation for launching much more detailed Robo advisor segmented types of service and product offerings. Because of the broad array of perspectives across the Robo advisor use intentions, the quantitative research needs to be stratified and robust enough to support the type of risk and the user design that delivers simplicity, clarity, and ease of use.

Research into Robo-advice is novel as limited research has been conducted in this area in the context of Western markets (Hentzen et al.,2022; Piehlmaier, 2022). Increased insights are required since research shows that the U.S. financial landscape differs from other countries where the use of Robo-advisors is widespread. Insights and lessons can be derived from the experiences of retail investors outside the U.S. abroad who have adopted Robo-advice. Analysis of performance indicators and experiences of foreign practices could inform the development of more precise guidelines for use by the financial planning industry. These guidelines could facilitate the incorporation of Robo-advisors into service offerings while causing minimal disruption to the traditional methods to which clients and financial planners are accustomed. From a managerial perspective, the findings suggest that additional attention needs to be devoted to adopting and inculcation AI and machine learning theories while building algorithms or logic to develop effective models (Bhatia et al., 2021).

Participants were cautiously expressed with the current risk profiling of investors. This presents insight for developers and designers of Robo-advisors on the need to include advanced and detailed programming to do risk profiling more comprehensively and precisely. Owing to the explorative nature of the study and limited participants, the study's findings cannot be generalized to the population. Future research is needed to study the dynamic nature of AI theories and investigate whether they can capture the sentiments of individual investors and the human sentiments impacting the market. In the future, Robo-advisors will eventually change the wealth management scenario. Technologies like Robo-advisors need to evolve further in predicting unstructured data, improvising the qualitative analysis technique to include the ability to gauge the emotions of investors and the market in real-time. In addition, the behavioral biases of both the programmers and investors will need to be taken care of while designing these automated decision support systems.,

Implications

Positive Social Change

Exploring information technology within different fields, including financial marketing, involves considering the low adoption of new services and platforms among investors. Empirical studies regarding the awareness of the Robo-advisory services, primarily within the American context, have not been fully explored in the finance or technology literature. In light of the recent technological developments, investors and experts call for further exploration and improvement on the current state of the Robo-services to serve investors in the United States.

Robo-advisors offer traditional investment management services at much lower fees than traditional financial advisors and are easy to use and secure(Brenner & Meyll, 2020). Customer service is a stronger driver of trust among traditional investors. Modern information technologies and the implementation of current and financial solutions have portrayed the potential of supporting the process of planning for personal finances through an automated advisor that makes decisions on behalf of the client. Currently, a problem with the widespread adoption of Robo-advisory services in Western nations remains, especially as compared with nations in Asia. Finance and technology scholars remain uncertain about how far the Robo-advisor trend will continue due to customer adoption barriers and challenges (Bhattia et al., 2021). By further understanding, retail investors' adoption intentions in using a Robo-advisor, the presne3t study may drive positive social change by offering recommendations to improve customer adoption of low-cost, automated financial management advice to a broader segment of new and intermediate investors.

Theoretical and Practice Implications

Finance and information technology scholars identified a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). Many studies on Robo-advisor adoption have been conducted in Asia; thus, more studies are needed to explore precursors of Robo-advisor adoption within Western financial market contexts to recommend future quantitative studies that will provide some generalizable findings (Atwal & Bryson, 2020; Gan et al. (2021).

Research studies on the diffusion of financial technology and Robo-advisors to customers were predominantly grounded in three adoption models: the Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model TAM) (Davis, 1985), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) (Atwal & Bryson, 2021). This study was significant to theory because it contributed original, qualitative data to the management and finance body of literature by extending the three adoption models explaining the diffusion of financial technology and Robo-advisors to customers for retail investment (Fan & Chatterjee, 2020; Hentzen et al.,2022).

Research findings demonstrate the awareness level of individual investors about the term “Robo-advisors” and their perception of the fintech phenomenon. The study also gives a perspective on the investors’ opinion of Robo-advisor and its functionality. The acceptance, intentions to use, and investors' perceptions of Robo-advisors have been widely researched empirically, but qualitative inquiries have been neglected. My study qualitatively explores American retail investors' attitudes, perceptions, opinions, and adoption intentions toward Robo-advisory services. Future research studies on Robo-advisory services may also explore regulation aspects and user design interfaces.

From a practitioner’s point of view, my study has implications for developing trust-building mechanisms, advanced risk profiling techniques, and data security platforms. Fintech awareness campaigns are generally missing from the American market today, and such developments may help Robo-advisory service providers and banks to address customers’ apprehensions about using Rrobo-advisor services. This study and other similar ones developed in the past two to three years have implications for the wealth management industry as a whole as it gives an insight into the qualitative factors of the customers' adoption intentions towards Robo-advisory services. There is a need for further scholarly research in both technology and finance on developing algorithms for AI and machine learning for risk assessment and risk profiling of investors, as mistrust and caution were the dominant trends driving low adoption intentions of Robo-advisory services.

Conclusions

The purpose of this qualitative, single case study with embedded units was to understand the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor. The global Robo-advisor market was valued at $4.51 billion in 2019 and is projected to reach $41.07 billion by 2027, growing at a compound annual growth rate of 31.8% from 2020 to 2027 (Statistica, 2021). Finance and information technology scholars wrote that there is a literature gap in understanding what factors drive investors in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (Piehlmaier, 2022; Zhang et al., 2021). While using Robo-advisors in financial institutions has become a popular trend, early adopters' identifed challenges may thwart the long-term success of this AI application to long-term use (Merkle, 2020; Tsai & Chen, 2022). Meeting this exploratory case study's purpose may address the literature gap on understanding customer adoption intentions in Western financial markets to use a Robo-advisor instead of a human advisor to manage their investments (see Piehlmaier, 2022; Zhang et al., 2021).

Robo-advisory is at a nascent stage and is still emerging and evolving. (Bhattia et al., 2021). My study is significant to professional practice to inform marketers when developing strategies to foster awareness and the intention to use and adopt Robo-advisors by retail investors within the United States. I conducted seven semistructured online interviews with retail investors in US market**s,** meeting the study’s inclusion criteria until data saturation. Multiple data sources were collected and triangulated to support trustworthy, qualitative results, including reflective journal notes and archival data from media sites on the adoption and use by customers of Robo-advisors within the US financial services industry (see Stake, 2010).

My study confirmed that all the participants had some risk aversion to using a Robo advisor, with their perceived risk level varying based on their past in-person and digital experiences, their level of financial and technological literacy, savviness/comfort, frequency of use, age, and overall socio-economic status. The study findings support that increased financial risk-taking is associated with using a Robo-advisor, as is having adequate financial literacy. All the participants expressed an explicit requirement that the Robo advisor interface be simple, clear, and straightforward to interact with and that the algorithms, rules, and recommendations be transparent and logical to understand.

My study results provide new, qualitative data and insights into US customers' intentions and describe barriers and facilitation recommendations. Participants expressed varying adoption intentions governed by their previous banking relationship experience, financial and technical literacy, confidence, frequency of use, age, and socioeconomic status. Every participant in the study also expressed the importance of banks and financial institutions must earn their trust by protecting their personal data through secure platforms and processes, as well as being able to customize the Robo advisor value proposition- services, products, offers, to their needs based on their relationship with the financial institution. By further understanding retail investors' adoption intentions in using a Robo-advisor, this study's results may drive positive social change by offering pathways to very low-cost, automated financial management advice to a broader segment of new and intermediate investors.

References

Abraham, F., Schmukler, S. L. & Tessada, J. (2019). *Robo-advisors: Investing through machines*, World Bank Policy Research Working Paper, (134881). https://ssrn.com/abstract=3360125

Accenture (2019), "The cost of cybercrime."https://www.accenture.com/_acnmedia/PDF-96/Accenture-2019-Cost-of-Cybercrime-Study-Final.pdf.

Adam, M., Wessel, M. and Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427-445. https://doi.org/10.1007/s12525-020-00414-7

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314-324. https://doi.org/10.1002/hbe2.195

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Akdeniz, Ö. O. (2022). Utilization of FinTech applications during the Covid-19 pandemic. In A. Petrillo, F. De Felice, M. V. Achim, & N. Mirza (Eds.), *Digital Transformation*. IntechOpen. https://doi.org/10.5772/intechopen.101796

American Customer Satisfaction Index. (2021). Retrieved December 24, 2021, from www.theacsi.org

Anshari, M., Almunawar, M. N., & Masri, M. (2022). Digital twin: Financial technology's next frontier of Robo-advisor. *Journal of Risk and Financial Management*, *15*(4), 163. MDPI AG. https://doi.org/10.3390/jrfm15040163

Atwal, G., & Bryson, D. (2021). Antecedents of intention to adopt artificial intelligence services by consumers in personal financial investing. *Strategic Change, 30*(3), 293-298. https://doi.org/10.1002/jsc.2412

Au, C. D., & Krahnhof, P. (2020). The role of robo-advisors in the German banking market–Critical analysis on human versus digital advisory services. *International Journal of Management and Applied Science*, *6*(8), 1-6. http://ijmas.iraj.in/paper_detail.php?paper_id=17393&name=The_Role_of_Robo-Advisors_in_The_German_Banking_Market_–_Critical_Analysis_on_Human_Versus_Digital_Advisory_Services

Baudewyn, N., & Draou, L. (2020). Robo-advisors in asset management: Towards a complete automation? [Master's thesis, Université catholique de Louvain]. DIAL.mem. http://hdl.handle.net/2078.1/thesis:24576

Belanche, D., Casaló, L.V. and Flavián, C. (2019). Artificial intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems, 119*(7), 1411-1430. https://doi.org/10.1108/IMDS-08-2018-0368

Ben-David, D., & Sade, O. (2020). Robo-advisor adoption, willingness to pay, and trust—Before and at the outbreak of the Covid-19 pandemic. https://ssrn.com/abstract=3361710

BETTER FINANCE. (2021, January 25). *Robo-advice 5.0: Can consumers trust robots?* https://betterfinance.eu/publication/robo-advice-5-0-can-consumers-trust-robots/

Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: A qualitative research to discover robo-advisory services. *Qualitative Research in Financial Markets*, *13*(5), 632-654. https://doi.org/10.1108/QRFM-10-2020-0199

Birkenmaier, J., & Fu, Q. (2016). The association of alternative financial services usage and financial access: Evidence from the National Financial Capability Study. *Journal of Family and Economic Issues, 37*(3), 450-460. https://doi.org/10.1007/s10834-015-9463-2

Boratyska, K. (2019). Impact of digital transformation on value creation in Fintech services: An innovative approach. *Journal of Promotion Management, 25*(5), 631-639. https://doi.org/10.1080/10496491.2019.1585543

Boustani, N. M. (2021). Artificial intelligence impact on banks clients and employees in an Asian developing country. *Journal of Asia Business Studies* (forthcoming). https://doi.org/10.1108/JABS-09-2020-0376

Breidbach, C. F., Keating, B. W., & Lim, C. (2020). Fintech: Research directions to explore the digital transformation of financial service systems. *Journal of Service Theory and Practice*, *30*(1), 79-102. https://doi.org/10.1108/JSTP-08-2018-0185

Brenner, L., & Meyll, T. (2020). Robo-advisors: A substitute for human financial advice?. *Journal of Behavioral and Experimental Finance, 25*, Article 100275. https://doi.org/10.1016/j.jbef.2020.100275

Castillo, D., Canhoto, A.I. and Said, E. (2020), “The dark side of AI-powered service interactions: exploring the process of co-destruction from the customer perspective”, Service Industries Journal, Vol. 41 Nos 13-14, pp. 900-925. https://doi.org/10.1080/02642069.2020.1787993

Chenail, R. J. (2011). Interviewing the investigator: Strategies for addressing instrumentation and researcher bias concerns in qualitative research. *Qualitative Report*, *16*(1), 255–262. https://eric.ed.gov/?id=EJ91404 http://www.nova.edu/ssss/QR/QR16-1/interviewing.pdf

Cheng, Y. M. (2020). Will robo-advisors continue? Roles of task-technology fit, network externalities, gratifications and flow experience in facilitating continuance intention. *Kybernetes, 50*(6), 1751-1783. https://doi.org/10.1108/K-03-2020-0185

Chhatwani, M. (2022). Does robo-advisory increase retirement worry? A causal explanation. *Managerial Finance, 48*(4), 611-628. https://doi.org/10.1108/MF-05-2021-0195

Chiu, I.H. (2019), “Transforming the financial advice market-the roles of Robo-advice, financial regulation and public governance in the United Kingdom”, Banking and Finance Law Review, Vol. 35 No. 1, pp. 9-35. https://discovery.ucl.ac.uk/id/eprint/10077662

Cooper, K., & White, R. E. (Eds.). (2012). *Qualitative research in the post-modern era*. Springer Netherlands. https://doi.org/10.1007/978-94-007-2339-9

DALBAR (2020). *Investor insights: COVID-19 and financial advice.* https://www.dalbar.com/catalog/product/165

Daniel, B. K. (2019). Using the TACT framework to learn the principles of rigour in qualitative research. *Electronic Journal of Business Research Methods*, *17*(3), pp118-129. https://doi.org/10.34190/JBRM.17.3.002

Daqar, M., Arqawi, S., & Karsh, S. (2020). Fintech in the eyes of Millennials and Generation Z (the financial behavior and Fintech perception). *Banks and Bank Systems*, *15*(3), 20-28. https://doi.org/10.21511/bbs.15(3).2020.03

Darskuviene, V., & Lisauskiene, N. (2021). Linking the robo-advisors phenomenon and behavioural biases in investment management: An interdisciplinary literature review and research agenda. *Organizations and Markets in Emerging Economies, 12*(2), 459-477. https://doi.org/10.15388/omee.2021.12.65

David, D., & Sade, O. (2019). Robo-Advisor Adoption, Willingness to Pay, and, Trust: An Experimental Investigation. SSRN. https://papers. ssrn. com/sol3/papers. Cfm .

Denzin, N. K., & Lincoln, Y. S. (Eds.). (2011). *The Sage handbook of qualitative research*. Sage Publications.

Elo, S., Kääriäinen, M., Kanste, O., Pölkki, T., Utriainen, K., & Kyngäs, H. (2014). Qualitative content analysis: A focus on trustworthiness. *SAGE Open*. https://doi.org/10.1177%2F2158244014522633

Fan, L., & Swarn, C. (2020). The utilization of robo-advisors by individual investors: An analysis using diffusion of innovation and information search frameworks. *Journal of Financial Counseling and Planning*. Advance Online Publication. https://doi.org/10.1891/JFCP-18-00078

Farquhar, J., Michels, N., & Robson, J. (2020). Triangulation in industrial qualitative case study research: Widening the scope. *Industrial Marketing Management*, *87*, 160–170. https://doi.org/10.1016/j.indmarman.2020.02.001

Fava, D. (2022). How well do robo-advisers need to know their clients?. *Journal of Financial Planning*, *35*(1), 57-59. https://www.proquest.com/openview/f23bd5fef2544a04ea8e50f5507c64d7/1?pq-origsite=gscholar&cbl=4849

Fernandes, T. and Oliveira, E. (2021), "Understanding consumers' acceptance of automated technologies in service encounters: drivers of digital voice assistants adoption", Journal of Business Research, Vol. 122, pp. 180-191. https://doi.org/10.1016/j.jbusres.2020.08.058

Fisch, J. E., Labouré, M., & Turner, J. A. (2019). The emergence of the robo-advisor. In J. Agnew & O. S. Mitchell (Eds.), *The disruptive impact of FinTech on retirement systems*. Oxford University Press.

Fisch, J. E., Laboure, M., Turner, J. A., & Center, P. P. (2017). The economics of complex decision making: The emergence of the robo adviser. *Recuperado de: http://www. geog. ox. ac. uk/events/170911/Robo-vs-Human-Advisers-Aug-28. Pdf* .

Gan, L. Y., Khan, M. T. I., & Liew, T. W. (2021). Understanding consumer's adoption of financial robo-advisors at the outbreak of the COVID-19 crisis in Malaysia. *Financial Planning Review, 4*(3), Article e1127. https://doi.org/10.1002/cfp2.1127

Gray, L. M., Wong-Wylie, G., Rempel, G. R., & Cook, K. (2020). Expanding qualitative research interviewing strategies: Zoom video communications. The Qualitative Report, 25(5), 1292–1301. https://nsuworks.nova.edu/tqr/vol25/iss5/9

Greve, G., & Meyer, F. (2021). Analysis of the use of robo-advisors as a replacement for personal selling. In P. Scholz (Ed.), *Robo-advisory: Investing in the digital age*. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-030-40818-3_6

Guba, E. G., & Lincoln, Y. S. (1994). Competing paradigms in qualitative research. In N. K. Denzin & Y. S. Lincoln (Eds.), *Handbook of qualitative research* (pp. 105–117). Sage. https://doi.org/10.1177/2158244014522633

Guion, L. A., Diehl, D. C., & McDonald, D. (2011). *Triangulation: Establishing the validity of qualitative studies* (Report No. FCS6014). Gainesville, FL: University of Florida Institute of Food and Agricultural Sciences (IFAS). http://edis.ifas.ufl.edu/fy394

Guo, L. Regulating Investment Robo-Advisors in China: Problems and Prospects. Eur Bus Org Law Rev 21, 69–99 (2020). https://doi.org/10.1007/s40804-020-00187-8

Halkias, D., & Neubert, M. (2020). Extension of theory in leadership and management studies using the multiple-case study design. *International Leadership Journal*, *12*(2), 48–73. https://doi.org/10.2139/ssrn.3586256

Hancock, D. R., & Algozzine, B. (2016). *Doing case study research: A practical guide for beginning researchers*. Teachers College Press.

Harkiolakis, N. (2017). *Quantitative research methods: From theory to publication.* Create Space. CreateSpace Independent Publishing Platform.

Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services: A systematic literature review and agenda for future research. *International Journal of Bank Marketing.* Advance online publication. https://doi.org/10.1108/IJBM-09-2021-0417

Hildebrand, C., & Anouk, B. (2021). Conversational robo advisors as surrogates of trust: Onboarding experience, firm perception, and consumer financial decision making. Journal of the Academy of Marketing Science, 49(4), 659-676. doi:https://doi.org/10.1007/s11747-020-00753-z

Insider Intelligence. (2021, June 30). *Young investors drove use of robo-advisors during pandemic*. https://www.insiderintelligence.com/newsroom/index.php/young-investors-drove-use-of-robo-advisors-during-pandemic/

Jaiwant, S. V. (2022). Artificial intelligence and personalized banking. In V. Garg & R. Goel (Eds.), *Handbook of research on innovative management using AI in industry 5.0* (pp. 74-87). IGI Global. https://doi.org/10.4018/978-1-7998-8497-2.ch005

Jung, D., Dorner, V., Weinhardt, C., & Pusmaz, H. (2018). Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets, 28*(3), 367-380. https://doi.org/10.1007/s12525-017-0279-9

Kavuri, A. & Milne, A. (2019). *Fintech and the future of financial services: What are the research gaps?* (CAMA Working Paper No. 18/2019). http://dx.doi.org/10.2139/ssrn.3333515

Komulainen, H., Saraniemi, S., Ulkuniemi, P., & Ylilehto, M. (2018). End-customer value restructuring the financial service supply chain. *Marketing Intelligence & Planning, 36*(6), 709-720. https://doi.org/10.1108/MIP-11-2017-0320

Kornbluh, M. (2015). Combatting challenges to establishing trustworthiness in qualitative research. *Qualitative Research in Psychology*, *12*(4), 397–414. https://doi.org/10.1080/14780887.2015.1021941

Korstjens, I., & Moser, A. (2018). Series: Practical guidance to qualitative research. Part 4: Trustworthiness and publishing. *European Journal of General Practice*, *24*(1), 120–124. https://doi.org/10.1080/13814788.2017.1375092

Kozinets, R. (2017). Netnography: Radical participative understanding for a networked communications society. In C. Willig & W. Stainton Rogers (Eds.), *The SAGE handbook of qualitative research in psychology* (p. 374). Sage Publications.

Kumar, R. (2019). *Research methodology: A step-by-step guide for beginners*. Sage Publications Limited.

Kvale, S. (1995). The social construction of validity. *Qualitative Inquiry*, *1*(1), 19–40. https://doi.org/10.1177/107780049500100103

Lee, J. M., & Hanna, S. D. (2015). Savings goals and saving behavior from a perspective of Maslow's hierarchy of needs. *Journal of Financial Counseling & Planning*, *26*(2), 129–147. https://doi.org/10.1891/1052-3073.26.2.129

Li, G., Field, J. M., & Davis, M. M. (2017). Designing lean processes with improved service quality: An application in financial services. *The Quality Management Journal*, *24*(1), 6-19. http://dx.doi.org/10.1080/10686967.2017.11918497

Lightbourne, J. (2017), “Algorithms and fiduciaries: existing and proposed regulatory approaches to artificially intelligent financial planners”, Duke Law Journal, Vol. 67 No. 3, pp. 651-679.

Lincoln Y., & Guba E. (1985). *Naturalistic inquiry*. Beverly Hills, CA: Sage. https://journals.sagepub.com/reader/content/177d1aa2de8/10.1177/1362168820941288/format/epub/EPUB/xhtml/index.xhtml#bibr1-1362168820941288:~:text=Lincoln%20Y.%2C%20Guba%20E.%20(1985).%20Naturalistic%20inquiry.%20Beverly%20Hills%2C%20CA%3A%20Sage.

Loos, B., Previtero, A., Scheurle, S., & Hackethal, A. (2020). *Robo-advisers and investor behavior* (Working paper). University of Technology of Sydney. https://www.professors.wi.tum.de/fileadmin/w00bca/digitalfinance/pdf/RoboAdvisers.pdf

Manser Payne, E., Dahl, A., & Peltier, J. (2021). Digital servitization value co-creation framework for AI services: A research agenda for digital transformation in financial service ecosystems. *Journal of Research in Interactive Marketing, 15*(2), 200–222. https://doi.org/10.1108/JRIM-12-2020-0252

Martin, W., & Davari, A. (2017). *Examining financial risk tolerance via the hierarchy of retirement needs* [Paper presentation]. Society for Marketing Advances (SMA) Annual Conference, Louiseville, Kentucky, USA.

Mbama, C. I., Ezepue, P., Alboul, L., & Beer, M. (2018). Digital banking, customer experience and financial performance: UK bank managers’ perceptions. *Journal* *of Research in Interactive Marketing, 12*(4), 432-451. https://doi.org/10.1108/JRIM-01-2018-0026

McKinsey & Company (2020), “AI-bank of the future: can banks meet the AI challenge?”, available at: https://www.mckinsey.com/industries/financial-services/our-insights/ai-bank-of-the-future-canbanks-meet-the-ai-challenge.

Menon, M. M., & Ramakrishnan, H. S. (2021). An empirical analysis of the factors influencing the adoption of robo-advisory in wealth management. *Information Technology in Industry, 9*(3), 560-566. http://www.it-in-industry.org/index.php/itii/article/view/593

Merkle, C. (2020). Robo-advice and the future of delegated investment. *Journal of Financial Transformation*, *51*, 20-27. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3612986

Merriam, S. B., & Grenier, R. S. (Eds.). (2019). *Qualitative research in practice: Examples for discussion and analysis.* John Wiley & Sons.

Merriam, S. B., & Tisdell, E. J. (2015). *Qualitative research: A guide to design and implementation*. John Wiley & Sons.

Metzler, D., Neuss, N., & Torno, A. (2022). The digitization of investment management–An analysis of robo-advisor business models. In *Wirtschaftsinformatik 2022 Proceedings*. https://aisel.aisnet.org/wi2022/finance_and_blockchain/finance_and_blockchain/2

Morgan, S. J., Pullon, S. R. H., Macdonald, L. M., McKinlay, E. M., & Gray, B. V. (2017). Case study observational research: A framework for conducting case study research where observation data are the focus. Qualitative Health Research, 27(7), 1060–1068. https://doi.org/10.1177/1049732316649160

Nassaji, H. (2020). Good qualitative research. Language Teaching Research, 24(4), 427–431. https://doi.org/10.1177/1362168820941288

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., & Agha, R. (2020). The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *International Journal of Surgery, 78,* 185–193. https://doi.org/10.1016/j.ijsu.2020.04.018

Noor, K. B. M. (2008). Case study: A strategic research methodology. *American Journal of Applied Sciences*, *5*(11), 1602-1604. https://doi.org/10.3844/ajassp.2008.1602.1604

Norlyk, A., & Harder, I. (2010). What makes a phenomenological study phenomenological? An analysis of peer-reviewed empirical nursing studies. *Qualitative Health Research*, *20*(3), 420–431. https://doi.org/10.1177/1049732309357435

Northey, G., Hunter, V., Mulcahy, R., Choong, K. and Mehmet, M. (2022), "Man vs machine: how artificial intelligence in banking influences consumer belief in financial advice", International Journal of Bank Marketing, Vol. 40 No. 6, pp. 1182-1199. https://doi.org/10.1108/IJBM-09-2021-0439

Palaganas, E. C., Sanchez, M. C., Molintas, V. P., & Caricativo, R. D. (2017). Reflexivity in qualitative research: A journey of learning. *Qualitative Report*, *22*(2), 426–438. http://dspace.upb.edu.ph/jspui

Phoon, K., & Koh, F. (2018). Robo-advisors and wealth management. The Journal of Alternative Investments, 20(3), 79-94. doi:https://doi.org/10.3905/jati.2018.20.3.079

Piehlmaier, D.M. (2022). Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice. Financ Innov 8, 14. https://doi.org/10.1186/s40854-021-00324-3

Oehler, A., Horn, M., & Wendt, S. (2021). Investor characteristics and their impact on the decision to use a robo-advisor. *Journal of Financial Services Research*, 1-35. https://doi.org/10.1007/s10693-021-00367-8

Overton, L., & O'Mahony, L. F. (2018). Stakeholder conceptions of later-life consumer vulnerability in the financial services industry: Beyond financial capability? *Journal of Consumer Policy, 41*(3), 273-295. https://doi.org/10.1007/s10603-018-9375-2

Payne, E.H.M., Dahl, A.J. and Peltier, J.W. (2021a), "Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems", Journal of Research in Interactive Marketing, Vol. 15 No. 2, pp. 200-222. https://doi.org/10.1108/JRIM-12-2020-0252

Payne, E.H.M., Peltier, J. and Barger, V.A. (2021b), "Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms", Journal of Research in Interactive Marketing, Vol. 15 No. 1, pp. 68-85. https://doi.org/10.1108/JRIM-10-2020-0214

Piehlmaier, D.M. (2022). Overconfidence and the adoption of robo-advice: Why overconfident investors drive the expansion of automated financial advice. *Financial Innovation*, *8*(14). https://doi.org/10.1186/s40854-021-00324-3

Reuter, J., & Richardson, D. P. (2022). New evidence on the demand for advice within retirement plans (No. w30261). National Bureau of Economic Research. http://www.nber.org/papers/w30261

Robinson, O. C. (2014). Sampling in interview-based qualitative research: A theoretical and practical Guide. *Qualitative Research in Psychology*, *11*(1), 25–41. https://doi.org/10.1080/14780887.2013.801543

Roth, W. M., & Von Unger, H. (2018, September). Current perspectives on research ethics in qualitative research. In Forum qualitative sozialforschung/forum: Qualitative social research (Vol. 19, No. 3, pp. 1-12). DEU.

Rühr, A. (2020). Robo-advisor configuration: An investigation of user preferences and the performance-control dilemma. In *Proceedings of the 28th European Conference on Information Systems (ECIS).* https://aisel.aisnet.org/ecis2020_rp/94/

Sadvandi, S., & Halkias, D. (2019). Challenges of human factors engineering in the coming transition to autonomous vehicle technologies: A multiple case study. The ISM Journal of International Business, 3(1), 3-8. https://www.ism.edu/images/ismdocs/ism-journal/ISM-Journal-2019.pdf

Saldana, J. (2016). *The coding manual for qualitative researchers* (3rd ed.). Sage Publications.

Scholz, P. (Ed.). (2020). *Robo-advisory: Investing in the digital age*. Palgrave Macmillan.

Shaheen, M., Pradhan, S., & Ranajee. (2019). Sampling in qualitative research. In M. Gupta, M. Shaheen, & K.P. Reddy (Eds.), *Qualitative Techniques for Workplace Data Analysis*, 25-51. IGI Global.

Shenton, A. K. (2004). Strategies for ensuring trustworthiness in qualitative research projects. *Education for Information*, *22*(2), 63–75. https://doi.org/10.3233/EFI-2004-22201

Sidat, S., & Matchaba-hove, T. (2021). Factors influencing the intentions of financial planners to adopt robo-advisors. *The Business & Management Review*, *12*(1), 141-152. https://www.proquest.com/openview/fcf6699c28d2c6ff1231440fe26ee7cb/1?pq-origsite=gscholar&cbl=2026610

Singh, N., Benmamoun, M., Meyr, E., & Arikan, R. H. (2021). Verifying rigor: analyzing qualitative research in international marketing. International Marketing Review. https://doi.org/10.1108/IMR-03-2020-0040

Stake, R. E. (1995). *The art of case study research*. Sage.

Stake, R. E. (2008). Qualitative case studies. In N. K. Denzin & Y. S. Lincoln (Eds.), *Strategies of qualitative inquiry* (pp. 119–149). Sage Publications.

Stake, R. E. (2010). *Qualitative research: Studying how things work*. Guilford Press.

Statista (2021*). Robo-advisors*. https://www.statista.com/outlook/dmo/fintech/digital-investment/robo-advisors/worldwide?currency=usd

Stenfors, T., Kajamaa, A., & Bennett, D. (2020). How to … assess the quality of qualitative research. *The Clinical Teacher*, *17*(6), 596–599. https://doi.org/10.1111/tct.13242

Stokes, Y., Vandyk, A., Squires, J., Jacob, J.-D., & Gifford, W. (2019). Using Facebook and LinkedIn to recruit nurses for an online survey. *Western Journal of Nursing Research*, *41*(1), 96–110. https://doi.org/10.1177/0193945917740706

Stone, A., & Harkiolakis, N. (2022). Technology Boom (ers): How US Multinational Technology Companies Are Preparing for an Ageing Workforce. *Administrative Sciences*, 12(3), 91. https://doi.org/10.3390/admsci12030091

Torno, A., Metzler, D. R., & Torno, V. (2021). Robo-what?, Robo-why?, Robo-how?–A systematic literature review of robo-advice. In *Pacific Asia Conference on Information Systems (PACIS) 2021 Proceedings.* https://aisel.aisnet.org/pacis2021/92

Torraco, R. J. (2016). Writing integrative literature reviews: Using the past and present to explore the future. *Human Resource Development Review*, 15(4), 404–428. https://doi.org/10.1177/1534484316671606

Tracy, S. J. (2019). *Qualitative research methods: Collecting evidence, crafting analysis, communicating impact.* John Wiley & Sons.

Tsai, S. C., & Chen, C. H. (2022). Exploring the innovation diffusion of big data robo-advisor. *Applied System Innovation*, *5*(1), 15. https://doi.org/10.3390/asi5010015

Venkatesh, V. (2021). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641–652. https://doi.org/10.1007/s10479-020-03918-9

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Warchlewska, A., & Waliszewski, K. (2020). Who uses robo-advisors? The Polish case. *European Research Studies Journal, 23*(Special issue 1), 97-114. https://www.um.edu.mt/library/oar/handle/123456789/76481

Wexler, M. N., & Oberlander, J. (2021). Robo-advisors (RAs): The programmed self-service market for professional advice. *Journal of Service Theory and Practice*, *31*(3), 351-365. https://doi.org/10.1108/JSTP-07-2020-0153

Yazan, B. (2015). Three approaches to case study methods in education: Yin, Merriam, and Stake. *The Qualitative Report*, *20*(2), 134–152. https://nsuworks.nova.edu/tqr/

Yin, R. K. (2017). *Case study research: Design and methods* (6th ed.). Sage Publications.

"Young Investors Drove Use of Robo-Advisors During Pandemic". (2021, June 30). *Insider Intelligence.* https://www.insiderintelligence.com/newsroom/index.php/young-investors-drove-use-of-robo-advisors-during-pandemic/#:~:text=The%20UK%20is%20slightly%20less,the%2055.6%25%20growth%20in%202020 .

Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. *Journal of Services Marketing, 35*(5), 634-646. https://doi.org/10.1108/JSM-05-2020-0162

Appendix A: Recruitment Letter

Hello,

I am a doctoral student at Walden University, and I invite you to participate in my research study. The purpose of this qualitative, single case study with embedded units is to understand the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor.

The study is critical as the findings can help inform how financial services providers design and deliver artificial intelligence automated interfaces, which can change how banking, insurance, investment, and other related industry services are used and managed. I believe your experience would be a significant contribution to the study. If you would be interested in participating in this study, the signed consent must be returned to the researcher via email or indicate your consent by typing "I Consent" to the researcher via email.

Thank you in advance for your consideration.

Respectfully,

Deborah Wall

Ph.D. Candidate – Walden University

Appendix B: Interview Protocol

Participant No: ______
Gender: _____
Age: _______
Profession: __________
Location: ___________
Years' experience using a Robo-advisor: ________

Preliminary Actions:

Interviewer to participants: Thank you for accepting my invitation. The purpose of this qualitative, single case study with embedded units is to understand the adoption intentions of retail investors in US markets to use a Robo-advisor instead of a human advisor.

Before we get started and ensure consistency among participants' interview responses, I would like to share the definitions of terms we may use within the interview process as they are defined within this study.

***Robo-advisor*:** This term refers to an AI-driven virtual financial advisor that provides investors with access to low-cost products and high-quality financial advice (Wexler & Oberland, 2020).

Adoption intentions: This term refers to the planned use or non-use of Robo-advisors by retail investors (Atwal and Bryson, 2021).

Retail investors: This term refers to consumers who invest their assets/money directly through a retail bank or wealth management investment company through a financial advisor or directly to a digital interface (Atwal and Bryson, 2021).

If you should need clarification on any question's content, please feel free to ask me to explain responding. Periodically I may ask clarifying questions or encourage you to describe in more detail. You are invited to elaborate where you feel comfortable and decline when you do not have information to add.
Before we begin the interview, you must be comfortable in your location and you feel free to participate without interruptions. Do you feel this description describes your setting at this moment?

May I begin the interview?

Awareness

1. How familiar are you with Robo-advisory services (in a general and regulatory context) for the retail investment customer?

Cost-effectiveness/perceived use

2. Would you consider Robo-advisors as a cost-effective alternative in the advisory Domain and why?

Trust/Attitude of use

3. Would you place higher trust in a Robo-advisor than a human financial advisor, and why?

Risk profiling

4. How do you perceive Robo-advisors (and their effectiveness) with respect to analyzing your level of risk?

Behavioral biases/usefulness

5. How confident are you that Robo-advisors have the potential to make an objective decision and address behavioral biases you may have as an investor?

Prediction and judgment

6. How confident are you about on the prediction and judgment capability of Robo-advisors?

Emotions

7. How do you believe Robo-advisors be able to manage the emotions of investors?

Data security

8. How confident are you about the security of your financial data when it comes to machines?

Adoption intention

9. Can you elaborate on your intention to continue using or not using Robo-Advisor services for retail investment advice?

Final thoughts

10. In closing this interview, would you care to add more thoughts on your adoption intentions to use a Robo-advisor instead of a human advisor?

Thank you for assisting me with this research study. I will contact you via email once the transcription of our interview is finalized. I will provide a summary of the interview, and I would like you to review the summary to confirm that I have captured the essence of what you have shared with me. If any discrepancies are found, I will correct the interpretations. Do you have any questions? Please contact me if you have any questions.