Design, Development, and Evaluation of an Artificial Intelligence-Enabled Chatbot for Honors College Student Advising in Higher Education

Reginald Saint-Aude Lucien
University of South Florida

Follow this and additional works at: https://digitalcommons.usf.edu/etd

Part of the Instructional Media Design Commons

Scholar Commons Citation
https://digitalcommons.usf.edu/etd/9592

This Dissertation is brought to you for free and open access by the USF Graduate Theses and Dissertations at Digital Commons @ University of South Florida. It has been accepted for inclusion in USF Tampa Graduate Theses and Dissertations by an authorized administrator of Digital Commons @ University of South Florida. For more information, please contact scholarcommons@usf.edu.
Design, Development, and Evaluation of an Artificial Intelligence-Enabled Chatbot for Honors College Student Advising in Higher Education

by

Reginald Saint-Aude Lucien

A dissertation submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in Curriculum and Instruction with a concentration in Instructional Technology Department of Educational Psychological Studies College of Education University of South Florida

Major Professor: Sanghoon Park, Ph.D. Tom Miller, Ed.D. David Lamb, Ph.D. James Hatten, Ph.D.

Date of Approval: March 26, 2021

Keywords: Academic Advising, Chatbots, HPT, Technology Acceptance Model (TAM)

Copyright © 2021, Reginald Saint-Aude Lucien
ACKNOWLEDGMENTS

First and foremost, I want to thank God before all else for being always present in my life. I thank my parents for all their sacrifice, love, and support. Without my mom and dad, this accomplishment would not be possible. There are so many incredible individuals who have supported me throughout my academic journey. I would like to start by highlighting two of those people. Dr. Stuart Silverman is the man who planted the seeds, encouraging me to pursue a PhD and always making me feel like family. Dr. Georg Kleine is a world-class storyteller and an incredible mentor even after retirement to countless numbers of students, including myself. I hope to bring some of Dr. Kleine’s passion for honors education into my professional practice.

I'm so fortunate to have a wonderful committee, full of leaders who have mentored me both in and out of the classroom. I first thank my major professor, Dr. Park, whose class led to the idea behind what developed into the AVA. Many thanks for your patience and kindness over the years. You're an incredible researcher, and I'm looking forward to continuing to learn so much from working with you. Dr. Miller, I've had the opportunity to know you for more than a decade and your leadership in student affairs as well as your wise counsel has always been appreciated. Dr. Hatten, your passion for teaching is something that I hope to emulate in my career moving forward. Your love for the content and your gift of captivating narratives are all things I hope to emulate in the future. A special thanks to Dr. Lamb for stepping in and supporting me in this process. I've greatly appreciated your kindness and your willingness to assist in any way possible. I would not be here today without these four individuals and their constant support and mentorship throughout this process.
A special thanks to the honors IT development team. These men and women are incredibly talented and I'm honored to work with them. Their talent allowed us to build something to be proud of out of very little and I will forever be grateful for this experience. There are so many people to thank who are both current and past colleagues. I thank all of my colleagues and co-workers who have provided encouragement and support throughout these past four years. I hope to do the same for them as they finish their PhD journeys.

Going through this journey requires sacrifice and incredible support from a strong foundation. Renae, you are my rock. Your support throughout this program and your steadfast love for our family cannot be overlooked. I would have never been able to do so much without an incredible partner and person by my side. Thank you for all you've done for me, our kids, and our family during these past five years. A special thanks to my Ari and Eliana, who have sacrificed time with their dad to allow him to pursue his dreams. You both are my heart and my joy. I can’t express with words how much I cherish all the support and love you have given to me.

I know there are many others who I have not mentioned here; I want to make sure you know all of your time and energies have not gone unnoticed and I give you my gratitude for everything.
# TABLE OF CONTENTS

## LIST OF TABLES

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>iv</td>
</tr>
</tbody>
</table>

## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>v</td>
</tr>
</tbody>
</table>

## ABSTRACT

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>vi</td>
</tr>
</tbody>
</table>

## CHAPTER ONE: INTRODUCTION

<table>
<thead>
<tr>
<th>Subsection</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction to the Problem</td>
<td>1</td>
</tr>
<tr>
<td>Problem Statement</td>
<td>5</td>
</tr>
<tr>
<td>Purpose of the Study</td>
<td>6</td>
</tr>
<tr>
<td>Justification for the Research</td>
<td>6</td>
</tr>
<tr>
<td>Research Questions</td>
<td>8</td>
</tr>
<tr>
<td>Significance of the Study</td>
<td>9</td>
</tr>
<tr>
<td>Definition of Terms</td>
<td>10</td>
</tr>
<tr>
<td>Conclusion</td>
<td>11</td>
</tr>
</tbody>
</table>

## CHAPTER TWO: LITERATURE REVIEW

<table>
<thead>
<tr>
<th>Subsection</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction of Concepts</td>
<td>13</td>
</tr>
<tr>
<td>Section 1: Academic Advising</td>
<td>13</td>
</tr>
<tr>
<td>Academic Advising Introduction</td>
<td>13</td>
</tr>
<tr>
<td>Historical Context of Academic Advising</td>
<td>15</td>
</tr>
<tr>
<td>The Role of Academic Advising</td>
<td>17</td>
</tr>
<tr>
<td>Academic Advising Standards</td>
<td>18</td>
</tr>
<tr>
<td>Academic Advising Strategies</td>
<td>19</td>
</tr>
<tr>
<td>Proactive Advising Strategy</td>
<td>21</td>
</tr>
<tr>
<td>Prescriptive Advising Strategy</td>
<td>21</td>
</tr>
<tr>
<td>Developmental Advising Strategy</td>
<td>22</td>
</tr>
<tr>
<td>The Unique Role of Honors Platforms</td>
<td>23</td>
</tr>
<tr>
<td>The History of Honors Platforms</td>
<td>23</td>
</tr>
<tr>
<td>What Makes an Honors Platform Different?</td>
<td>24</td>
</tr>
<tr>
<td>Challenges for Honors Students</td>
<td>25</td>
</tr>
<tr>
<td>Challenges for Honors Platforms and Academic Advising</td>
<td>26</td>
</tr>
<tr>
<td>Academic Advising within an Honors Platform</td>
<td>27</td>
</tr>
<tr>
<td>Demonstrated Need for Improved Efficiency in Academic Advising</td>
<td>28</td>
</tr>
<tr>
<td>Section 2: Human Performance Technology</td>
<td>29</td>
</tr>
</tbody>
</table>
CHAPTER THREE: METHODOLOGY .........................................................52

Section 1: Introduction ....................................................................................................................52
Research Questions .........................................................................................................................52
Participants .......................................................................................................................................52
Research Design ..............................................................................................................................54

Section 2: Design and Development of Advising Virtual Assistant Chatbot ................................55
HPT Process: Performance Analysis of Need and Opportunity .......................................................55
Organizational Analysis ..................................................................................................................55
Environmental Analysis ..................................................................................................................55
Desired Performance ......................................................................................................................56
Actual Performance .........................................................................................................................56
Gap Analysis .....................................................................................................................................57
Cause Analysis ...............................................................................................................................57

HPT Process: Interventions ............................................................................................................58
HPT Process: Evaluation of the Intervention ...................................................................................60
Data Collection Instruments ...........................................................................................................60
Study Procedure ..............................................................................................................................63
Data Analysis ...................................................................................................................................66
<table>
<thead>
<tr>
<th>CHAPTER FOUR: RESULTS</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction</td>
<td>72</td>
</tr>
<tr>
<td>Research Question 1</td>
<td>73</td>
</tr>
<tr>
<td>Research Question 2</td>
<td>75</td>
</tr>
<tr>
<td>Participant Usage (User Interaction Data)</td>
<td>79</td>
</tr>
<tr>
<td>Chatbot Performance</td>
<td>80</td>
</tr>
<tr>
<td>AVA Dialogue Flow</td>
<td>81</td>
</tr>
<tr>
<td>Research Question 3</td>
<td>82</td>
</tr>
<tr>
<td>TAM Survey Data Conclusion</td>
<td>87</td>
</tr>
<tr>
<td>Research Question 4</td>
<td>88</td>
</tr>
<tr>
<td>Conclusion</td>
<td>90</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>CHAPTER FIVE: DISCUSSION AND CONCLUSION</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction</td>
<td>92</td>
</tr>
<tr>
<td>Discussion of the Findings</td>
<td>93</td>
</tr>
<tr>
<td>Participants’ Interaction with AVA</td>
<td>94</td>
</tr>
<tr>
<td>TAM Survey Findings</td>
<td>96</td>
</tr>
<tr>
<td>Limitations</td>
<td>101</td>
</tr>
<tr>
<td>Implication of the Findings</td>
<td>101</td>
</tr>
<tr>
<td>Recommendations for Further Research</td>
<td>102</td>
</tr>
<tr>
<td>Conclusion</td>
<td>103</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>REFERENCES</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>105</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>APPENDIX 1: TECHNOLOGY ASSESSMENT MODEL (TAM) SURVEY</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>117</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>APPENDIX 2: HONORS PORTAL LANDING PAGE</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>118</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>APPENDIX 3: AVA CHATBOT DIALOGUE</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>119</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>APPENDIX 4: INITIAL AVA CONCEPTUAL DESIGN</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>120</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>APPENDIX 5: ITERATIVE AVA CHATBOT DESIGNED</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>121</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>APPENDIX 6: IRB APPROVAL LETTER</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>122</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>APPENDIX 7: PARTICIPANT SAMPLE QUESTIONS</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>123</td>
</tr>
</tbody>
</table>
LIST OF TABLES

Table 1: Key datasets for AVA usage .......................................................... 61
Table 2: The collected AVA data includes .................................................. 65
Table 3: Aligned research questions for data analysis ................................. 68
Table 4: Study participant demographics .................................................. 73
Table 5: Categories of questions most addressed by AVA ............................ 76
Table 6: TAM demographic information .................................................. 83
Table 7: Means and standard deviations of TAM items ............................... 83
Table 8: Means and standard deviations of perceived ease-of-use (by gender) ........... 84
Table 9: Means and standard deviations of perceived ease-of-use (by cohorts) ................. 85
Table 10: Means and standard deviations of perceived usefulness ..................... 85
Table 11: Means and standard deviations of intention to use ............................ 86
Table 12: Items that triggered incorrect AVA response intents ....................... 89
LIST OF FIGURES

Figure 1: Performance Improvement Using the HPT Model..........................................................35
Figure 2: Total AVA interactions by month and gender .................................................................74
Figure 3: A participant’s discussion about global experience .......................................................78
Figure 4: Chart showing participant retention based on conversation flow .................................81
Figure 5: A participant’s AVA academic advisor-related inquiry..................................................89
ABSTRACT

Academic advising is seen increasingly as an essential function supporting the educational mission of universities. Institutions have made significant investments supporting academic advisors and student success initiatives by leveraging technology resources such as Canvas and Degreeworks. There is a rising need for technology that can assist academic advisors in their responsibility to guide students along the path to academic success and AI resources that promote more efficient use of human capital are positioned to meet that need. Chatbot applications can serve as a technology-mediated intervention for delivering information and interactive content to support student success.

This study aimed to design, develop, and evaluate an automated, AI-enabled advising resource (the AVA chatbot) to deliver academic advising and university-related information in an honors college environment. Human Performance Technology (HPT) served as a framework throughout the study to shape the conversation around performance gaps, advising information delivery, and using chatbot technology as an intervention. During the organizational analysis, the HPT model provided a workflow for understanding the honors college values, mission, and vision. The study indicated that the AVA chatbot added value in the sharing of real-time data with advisors and that it was perceived as having acceptable response accuracy by participants. The real-time data visible to stakeholders and decision-makers offered a better understanding of students’ needs and was a benefit to students' wellbeing. The AVA data was successful at showing where information gaps existed and when students were asking questions relevant to their academic journey. Technology Assessment Model (TAM) survey data yielded valuable
insight into who used the chatbot and how participants engaged with it. Extracted AVA data contributed to addressing needs that were not met via university websites. The data also showed which student populations felt more supported by the AVA through their successful interaction with the chatbot. The AVA chatbot data illustrated opportunities for improvement to stakeholders and showed paths to addressing performance gaps. Additionally, the AVA data provided helpful insights about participants which helped to enhance the AVA chatbot and student portal site.

Finally, the researcher conducted a comprehensive evaluation to assess the appropriateness of the AVA’s responses to participant questions. Positive perceptions toward the AVA chatbot were evidenced by the data on perceived ease of use, perceived usefulness, and intention to use. Of these three survey categories, the AVA scored lowest on the intention to use and highest on perceived ease of use, with the majority of participants indicating they would use the AVA again.

The findings concluded that chatbots could help large and small higher education institutions effectively support their student populations by providing round-the-clock advising information as well as tracking and measuring overall contributions and pinpointing data insights in real-time. The implications of this study can be valuable to both technology implementation in higher education and chat application design and development.
CHAPTER ONE:
INTRODUCTION

Introduction to the Problem

Higher education places a strong focus on student retention (Bowman & Culver, 2018; Troxel, 2018; White, 2015), which cannot be successfully achieved without a well-established academic advising system. Academic advisors are mentors and coaches who facilitate academic success and serve as institutional representatives, giving “insight or direction to a college student about academic, social, or personal matters” (National Academic Advising Association [NACADA], 2014). Since its inception, the academic advising profession has guided the development of best practices to encourage student retention and persistence.

It could be said that academic advising started with faculty members, who have traditionally been seen as purveyors of knowledge, so students naturally gravitated towards them for general academic guidance. Over time, the role of faculty has evolved, with an increasing focus on curriculum and research (Wright & Horst, 2013). Due to the changing role of faculty, the need arose for a new group of professionals who were solely dedicated to providing guidance to support students on their academic journey. Chartered in 1977, The Global Community for Academic Advising, commonly known as NACADA, is a professional organization that formally recognizes the work done by faculty and staff in academic advising and supports the academic advising profession within higher education (Grites & Gordon, 2009). NACADA was the first to formally recognize academic advising as a profession in higher education.
Current trends in academic advising emphasize the importance of providing students with accurate and timely advising services as a measure of advising efficiency. According to the Council for the Advancement of Standards (CAS) (2018), there are three advising standards that support the use of technology with attention to sustainable, effective academic advising. These include: (1) technology must be used to enhance the delivery of academic advising services (2) advising programs must make sure technology addresses constituent needs, and (3) the use of technologies must facilitate user interactions with advising. Academic advisors are an essential resource for encouraging students’ engagement in higher education (Campbell & Nutt, 2008).

Academic advising is a process of helping students contextualize their educational experiences during their academic journey (Darling, 2015). According to CAS standards (2018), three advising areas are essential for engaging in shared responsibility for effective academic advising. The first essential behavior is to have the advisors engage students in the shared responsibility of academic advising. Second, advisors are tasked with the delivery of academic information, but are given flexibility to use various delivery mechanisms as long as they meet the needs of the student. The third and last essential behavior is that the advisors must provide their students a private and safe space to ask questions and share concerns.

Advisors’ responses should be accurate and understandable, allowing students to receive timely responses to their questions. However, there is multicausal deficit of advising services, including poor advisor-to-student ratios and departmental financial constraints (White, 2015). Also, from the student perspective, the advising process can be cumbersome and complex. Existing tools for academic advising information delivery include the university degree audit system, email, and websites, but these are not effective means by which to communicate needed information to students (Hause, 2017; VanDieren, 2018). After the advising office closes,
students must search through websites and rely on roommates for advising information, which often leads to misinformation and confusion.

Advising requires a considerable amount of planning on the part of both students and advisors (Feghali, Zbib, & Hallal, 2011). Especially, developmental advising involves services that should be accurate, convenient, and accessible at all hours of the day and night (Allen & Smith, 2006). Academic advisors working with honors college students are often challenged to meet the unique and complex needs of the honor student population (Scott & Frana, 2008). Huggett (2004) stated that honors students typically have early contact with their academic advisors, are open to communication through a multitude of venues, and are forward-thinking about academic and career plans. Since honors students go beyond seeking the high level of developmental advising (Kaczvinsky, 2007), advisors need to identify the most effective and efficient ways to communicate institutional policy and major requirements to maximize the available resources (Grites, 2013; Harris, 2018). Severely time-restricted advising appointments are limited to prescriptive advising information and fail to deliver the mentoring and coaching needed to holistically support students (Allen & Smith, 2006).

Minimizing time spent on prescriptive advising during advising appointments helps advisors to focus advising time on more holistic developmental advising. Prescriptive advising refers to the repetitive factual information which can be delivered well in an automated format. Henderson and Goodridge (2015) argued that automation will help to standardize the information delivered to all students, thus improving student engagement and student retention by minimizing inconsistencies. An Artificial Intelligence (AI)-based chatbot has been suggested as such an intervention that enables machines to perform tasks that were previously associated with human intelligence (Gardner, 2018). Chatbots are software programs that communicate with
multiple users via messaging at the same time and at any time of day (Chan, Lee, Lo, & Lui, 2018). The strengths of a chatbot application are its deployment ability, scalability, and efficiency for information sharing with users (Przegalinska, Ciechanowski, Stroz, Gloor, & Mazurek, 2019).

AI-infused chatbots effectively utilize natural-language processing via text or voice input from a user and generate quick and relevant responses for task-oriented or informal conversations in fields such as finance, law, and business (Georgescu, 2018; Srivastava, 2018). It is their ability to convincingly simulate how a human would behave as a conversational partner that separates chatbots from other resource tools. AI chatbot applications have a documented history of utility when considering their use in educational settings. Crayannopoulos (2017) stated chatbots and instant messaging share the ability to offer a quick conversation, general convenience, and ease-of-use, which have all been attributed to offering a greater sense of connection between students and advisors. The application of chatbot technology promises to improve academic advising by allowing advisors to better use their time to address the needs of higher education institutions and their students.

An AI-infused chatbot could be deployed into the academic advising practice to address issues of advising inefficiencies. Using information selected and prepared by academic advisors with area expertise, an Advising Virtual Assistant (AVA) chatbot can help students procure requested information through a more efficient, convenient, and reliable process by eliminating the frustrations of scanning through multiple pages of websites. This study addresses the innovative approach of advising automation by describing the design and development process of an AVA chatbot system, and further evaluating the effectiveness of the system in a higher education setting. The AVA chatbot aims to deliver prescriptive, time-flexible advising services,
so as to increase advising efficiency and provide academic advisors more time to meet the more complex advising needs of their students and the overarching goals of the university.

First, this study employed the Human Performance Technology (HPT) model to assess the academic advising needs of an honors college. The performance gap between the current advising practice and the desired advising practice were compared in relation to two of the three CAS Standards (2018): advising accuracy and around-the-clock availability of personalized prescriptive advising information. The process involved identifying organizational and environmental factors currently impacting prescriptive academic advising. HPT follows a systematic process of discovering and analyzing an essential human performance gap (Kang & Molenda, 2018). Performance technology provides a holistic approach to understanding human potential by fine-tuning performance drivers that can contribute to the development of human capital (Surry & Stanfield, 2008). Within HPT, practitioners create a blueprint that focuses on solving problems, enlightens the participative nature of human interaction, and utilizes systematic inquiry processes for holistic solutions. Creating these blueprints relies upon empirical research to improve human performance or reach desired performance levels through various scientific approaches and evidence (Klein, 2002).

The needs analysis results from the HPT method informed the design and development of an AVA chatbot system. Evaluation of the system involved student perceptions of academic advising based on their experiences with the AVA chatbot. The cause analysis helped to narrow the specific area the chatbot intervention would address. 

Problem Statement

To improve student persistence and retention, which are important goals within higher education (Tight, 2020; Zhang, Gossett, Simpson, & Davis, 2009), a new and innovative
advising method needs to be considered in higher education. One such innovation is to creatively automate the delivery of prescriptive advising information. Henderson and Goodridge (2015) described automation of advising as the automated delivery of academic advising information. Higher education places a focus on student retention, expecting that academic advisors will facilitate these goals. Advisors need more support in order to maximize their impact on students. Evidence shows a need for supportive technology for academic advisors.

**Purpose of the Study**

This study aimed to design, develop, and evaluate an automated, AI-enabled, advising resource (the AVA chatbot) for delivery of academic advising and university-related information in higher education. The AI-enabled AVA chatbot was designed to deliver prescriptive advising information to honors college students by allowing them to access needed information in a timely manner and enabling them to make decisions that will assist them in academic persistence. Data on students’ perception of the AVA chatbot system and students’ usage information from the chatbot application yielded valuable data on the AVA chatbot’s ability to deliver prescriptive academic advising support.

**Justification for the Research**

To understand today’s higher education environment, it is important to comprehend current university funding resources. Universities are under tremendous pressure to compete for limited funds. Therefore, tools that offer institutions the opportunity to save money are highly desirable (Gardner, 2018). Academic advising is seen increasingly as an essential function of supporting the academic mission of universities. Institutions have made great investments in supporting student success initiatives by leveraging technology resources such as Canvas and Degreeworks to support academic advisors.
The rapid increase of technology resources in higher education over the past decade has made higher education a fertile ground for cutting-edge technologies (Gardner, 2018). AI is being incorporated into everything from smart speakers to cell phones, and now educational software (Carayannopoulos, 2017). There is a rising need for technology to assist academic advisors in their responsibilities to guide students along the path to academic success, such as leveraging AI resources to promote more efficient use of human capital. Academic advisors provide a high level of guidance to ensure students are able to successfully complete their degree programs. Student success in terms of retention and persistence metrics are used to evaluate funding, allocate resources, and evaluate institutional effectiveness (Troxel, 2018). Successful academic advising fosters a heightened sense of personal investment on both the parts of the academic advisor and the student (Yarbrough, 2002). This sense of personal investment is integral to helping students succeed, thereby supporting university mission statements.

However, with the growing population of students in higher education, academic advisors increasingly find themselves relying on prescriptive advising while overlooking students’ individual needs (Lynch & Lungrin, 2018). Harris (2018) stated that prescriptive advising is a limited form of an advising session that provides the information necessary for progression. Accessing in-person academic advising can be complicated for non-traditional students who, in addition to classes, are juggling work and family and may not be able to easily schedule advising appointments. Larger departments may have 2 to 4-week waiting times for advising appointments and often students are unable to get the answers they need in a timely manner, which may impact their ability to meet university deadlines. With academic advisors balancing student ratios greater than 200 to 1, it becomes difficult for them to provide individualized consultations addressing the specific needs of each student (Nwankwo, 2018).
Academic advising approaches play an important role in allowing advisors to develop meaningful, trusting relationships with students. The developmental approach of advising has been offered as a way to give more individualized attention to each student with a strong emphasis on mentorship. This engagement approach requires an even more concentrated effort on the part of the academic advisor to help students pursue goals and objectives (Yarbrough, 2002). With limited resources and great demand for professional advisors due to high enrollment numbers, the time is right for leveraging chatbot technology as an academic advising resource. Therefore, the purpose of this study was to design, develop, and evaluate the AVA chatbot system for honors college student advising in higher education.

**Research Questions**

1. What are the demographics of students who use the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?

2. How are students using the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?

3. How do students perceive an Advising Virtual Assistant (AVA) chatbot as a tool for answering their academic advising questions?

4. How efficient was the Advising Virtual Assistant (AVA) chatbot at addressing prescriptive academic advising questions?

The above research questions were examined through quantitative data collection and analysis, using a survey and AVA application data. To address the first question, detailed demographics behind who used the AI-enabled AVA chatbot were collected. The second question analyzed participants’ various usage data, which was automatically gathered by the AVA chatbot system. For the third question, a survey was administered to study participants’
perception of the AVA chatbot as an advising tool. The fourth question examined the AVA’s efficiency in addressing prescriptive advising questions.

**Significance of the Study**

Prior work related to the implementation of online academic advising chatbot applications have proven to be successful by providing around-the-clock advising services to a large number of users (Ho, Lee, Lo, & Lui, 2018). Previous studies have typically focused on the implementation of natural language-based chatbots from an engineering perspective. Previous chatbot design literature has focused on attempting to create algorithms that emulate human conversation using popular codebase such as ALICE and other technologies (Ghose & Barua, 2013). Even when researchers have created advising-based chatbot systems, they typically focus on the technologies that they have created as opposed to the communicative style that these bots attempt to simulate.

The design and logical flow are important when building a robust conversational chatbot (Brandtzaeg & Folstad, 2017). The researcher looked at the design and implementation of a conversational chatbot from an advising perspective. This study is significant because an academic advising practitioner was involved in the chatbot design and curation of information incorporated in the chatbot. A focus on prescriptive advising and curating academic advising information within the knowledge database supporting a chatbot has not been seen in academic literature to the knowledge of this researcher.
Definition of Terms

**Academic advising:**

Mentoring students on their academic journey by providing appropriate strategies for addressing the needs and concerns of the student while continuing to support the goals and mission of the institution.

**Chatbots/conversational agents:**

ELIZA was a computer with specialized software that mimics natural language in human-oriented conversations (Weizenbaum, 1966). This chatbot, was capable of analyzing sentences input based on reassembly rules associated with a decomposition of the input (Kerlyl, Hall, & Bull, 2006). Chatbot applications can be designed to use natural language in conversation with a person to have efficient and personalized communication. ELIZA used syntactic language processing which has since been further developed, prompting the design of various language processing chatbots (Kerlyl et al., 2006). A.L.I.C.E., originally built in 1995, is a successor to ELIZA and in a 2001 rewrite, developers added Artificial Intelligence Markup Language (AIML) to her program (Wallace, 2003). The concept of natural language allows users without the knowledge of computer code to input requests into the software.

**Developmental advising approach:**

Supports student understanding of what college is about with a focus on the reasons why majors or career pathways are selected. This style of advising is designed to help educate the whole student and has a focus on student growth beyond cognitive factors (He & Hutson, 2016).
Honors platform: Includes both departmental honors programs and institutional honors colleges that have the same underlying premise built around providing a liberal arts education with additional learning opportunities for high-achieving, academically minded students to enhance their undergraduate experience (Wawrzynski, Madden, & Jensen, 2012).

NACADA: The Global Community for Academic Advising: A professional organization that formally recognizes the work done by faculty and staff in academic advising and supports the academic advising profession within higher education (Grites & Gordon, 2009).

Prescriptive advising approach: Prescriptive advising addresses academic requirements for degree completion and graduation. It is prescriptive in nature because the academic advising practitioner is giving information in an authoritative manner (Walters, 2016).

Proactive advising model: This academic advising approach was formerly known as intrusive advising and aims to reduce student attrition due to academic failure (Varney, 2007). In this approach, advisors proactively engage with the student to better support their academic journey.

Conclusion In the current landscape of academic advising, increasing demands on time and resources have only limited advisors’ ability to truly support students in accomplishing their goals. The promise of using chatbots within academic advising has the potential to provide a more efficient process that will encourage progress to degree completion. HPT served as the model to perform an analysis of both current and desired performance within academic advising and identify
performance gaps. Chatbot applications can serve as a technology-mediated intervention for delivering information and interactive content to impact student success. In the setting of academic advising, chatbots offer an extension of academic advising resources beyond traditional office hours, thereby increasing student access to information and improving student support resources. The goal of this study was to improve efficiency and quality of academic advising within an honors college context. By improving the quality and efficiency of academic advising processes, academic advisors are empowered to focus on complex student needs which will ultimately benefit student persistence and retention.
CHAPTER TWO:
LITERATURE REVIEW

Introduction of Concepts

This study explores the relationship between Human Performance Technology (HPT), chatbot applications, and academic advising. HPT is a tool for assessing and improving environments which can be implemented within academic advising, using chatbot technology as a vehicle to narrow performance gaps. This literature review seeks to understand whether the current constructs of academic advising can be modified for improved efficiency in terms of delivery of prescriptive academic advising to undergraduate honors college students. In order to create a more efficient prescriptive academic advising delivery system, a better understanding is required of academic advising, HPT, and chatbot technology; this chapter will serve as an in-depth literature review focusing on these topics.

Section 1: Academic Advising

Academic Advising Introduction

There is research available on academic advising from professional advising organizations dedicated to the academic advising profession (NACADA, 2014). However, these sources do not provide consistently high-quality research on academic advising. There is a plethora of research available on academic advising strategies and how advising contributes positively towards student persistence (Fosnacht, McCormick, Nailos, & Ribera, 2017; Grites, 2013; Hause, 2017; Harris, 2018; Leach & Patall, 2016; Miller & Woycheck, 2003; VanDieren, 2013; Hause, 2017; Harris, 2018; Leach & Patall, 2016; Miller & Woycheck, 2003; VanDieren,
Articles exist on student perspectives and experiences within academic advising. Student perspective/experience is one evaluative tool used to assess the quality of academic advising services (Allen & Smith, 2006; Anderson, Motto & Bourdeaux, 2014; Smith, 2002; Walters, 2016).

To the researcher’s knowledge, there is not any available research on the efficiency of academic advising processes. Available research does not document the frequency of academic advising appointments or interactions, but there are suggestions as to what would be an ideal advising cycle (Fosnacht, McCormick, Nailos, & Ribera, 2017; Walters, 2016). Academic advising lacks a specific professional pathway, leading to a greater need to justify the importance of academic advising as a career (Shaeffer, Zalewski, & Leveille, 2010).

More research is needed to illustrate the complex skill sets required to be a successful academic advisor. Academic advisors do so much more than just helping students pick the correct classes. Academic advisors motivate, challenge, and guide students on their academic and professional paths, while also imparting important institutional knowledge necessary for success within the higher education experience (Nwankwo, 2018; Campbell & Nutt, 2008; He & Hutson, 2016; Vianden, 2016; Viander & Barlow, 2015). The personal skills one brings to the profession are as important, perhaps more so, than the degree one has.

As a subsection of academic advising, more research is needed to understand honors colleges and honors students. One purpose of this research is to gain a better understanding of the specific characteristics of these students so that their unique advising needs can be addressed, ultimately aiding academic persistence (Johnson, Walther, & Medley, 2018; Huggett, 2004; Kaczvinsky, 2007; VanDeren, 2018).
Historical Context of Academic Advising

To examine honors college academic advising it is important to first understand the historical context behind the academic advising profession and how advising approaches have guided the development of best practices to encourage student retention and persistence. When looking at the history of academic advising, there are many specific instances where one could identify “the root” of academic advising in the historical lexicon of higher education. Here, the researcher identifies the root as the organization that formally recognized academic advising as a profession within higher education. This organization is The Global Community for Academic Advising (NACADA) and was chartered in 1977. NACADA recognizes and supports the efforts of faculty and staff in academic advising at institutions of higher education (Grites & Gordon, 2009).

Providing a clear and comprehensive definition for the field of academic advising has been a challenge. There have been multiple evolutions of academic advising since its initial conception and due to this evolving history, it is difficult to define the field at present day (McGill, 2019). Even NACADA has more than 17 definitions for academic advising (NACADA, 2014). A few of these definitions from the NACADA website include:

- Advising is a process by which advisors and advisees enter a dynamic relationship, respectful of the student’s concerns (O’Banion, 1972).
- Academic advising is a process which helps students identify their education or career goals and develop appropriate educational plans to realize them (Winston, Enders, & Miller, 1982).
- Academic advising goes beyond the administrative function of mapping degree plans and scheduling classes. Good academic advising guides students in clarifying personal and
career goals and regularly evaluates progress to those goals (The College of New Jersey, 2002).

- “Academic advising, along with teaching, research, and service is central to achieving the fundamental goals of higher education. Academic advising is an intentional educational process that requires concern for and consideration of all these fundamental goals” (Western New Mexico University, 2005, Western New Mexico University section).

Defining academic advising is, to a large degree, institutionally based because academic advising is positioned as an essential part of supporting both the learning and student success missions of a university (Campbell & Nutt, 2008). Thusly, academic advising at one institution may seek to satisfy goals and objectives that may not be necessary at a different institution. Knowing the historical context of how academic advising became a profession explains why there are so many different definitions of academic advising. The researcher’s definition of academic advising is to serve as a mentor to guide students on their academic journey by providing appropriate strategies for addressing the needs and concerns of the student while continuing to support the goals and mission of the institution.

This need for dedicated academic advisors was highlighted at the end of World War II with the return of many American service personnel, who were taking advantage of their GI Bill to go to college for the very first time. The addition of many more traditional and non-traditional students coming to campus at the same time presented a challenge for higher education. Grites (1977) stated during the 1950s, faculty moved away from advising due to being dissatisfied with the process and instead focused their time and energy on consultation and committee work to further efforts in research, publishing, and institutional governance.
Colleges continued to become more diverse and the number of students continued to increase. In the 1970s, the United States was going through an economic recession and the impacts of this recession were also felt in higher education. Due to financial constraints, a number of important issues were raised regarding student retention and persistence as well as the funding of higher education. Administrators began to tighten up their budgets and focused on addressing student retention and persistence by looking for ways to best support students so that they would academically succeed. From the returning military veteran to the racially diverse student, to the economically challenged student, universities were faced with the question of how to best support the students on campus (Grites, 1977). Subsequently, academic advising has continued to uphold the mission and vision of higher education institutions by exerting initiatives to support improved student persistence and retention via face-to-face interaction with individual students.

**The Role of Academic Advising**

From its inception, academic advising was designed to offer students support in academic, social, and personal matters (Shaffer, Zalewski, & Leveille, 2010). Strategically positioning academic advisors has worked. These professionals advocate for student needs and also serve as institutional representatives. At any given institution, academic advising is in direct support of institutional vision, policies, and curriculum (NACADA, 2017). In one study about perceptions on advising, students highlighted that they felt advisors were not working in their best interests but in the interest of the advisor/institution (Noaman & Ahmed, 2015). In working with college students, advisors are educators who teach students to develop academic goals and plans (Grites, 2013; Leach & Patall, 2016). At times, policies and procedures may impact what the advisor says in support of the students’ course selection or interest. Advisors serve as the first
line of defense when it comes to addressing student needs and disseminating information for policy and procedures because they have the ability to reach all students (Grites, 2013; Harris, 2018; Leach & Patall, 2016).

This institutional expectation places a burden of responsibility on the academic advising process. With an emphasis on degree completion and persistence, academic advisors play an important role in the lives of students. Higher education institutions continue to be under fire by state legislators to address retention and degree completion (White, 2015). University administrators have positioned academic advisors to address these issues because of the level of contact these professionals have with students. As a result, advisors use a number of different strategies to support students through their developmental growth, to promote academic persistence, and to build relationships with students. Vianden and Barlow (2015) stated that the relationships a student has with institutional representatives and his/her peers have the greatest impact on a student’s intention to persist.

**Academic Advising Standards**

The Council for the Advancement of Standards in Higher Education (CAS) states that academic advisors must provide students with clarification for institutional policies, provide accurate information regarding academic pathways, monitor academic progress, and connect students with appropriate resources to facilitate student success (CAS Standard, 2018). The CAS Standards serve as a framework to guide the academic advising profession. This document serves as a guiding principle to aid seasoned and new professional advisors in learning the essentials in relation to their professional roles. The standards provide guidance towards a number of areas addressing the work of an academic advisor, including topics from workspace procedures to
equipment acquisition, all with guided recommendations. These standards help to structure the
day-to-day activities of academic advisors.

**Academic Advising Strategies**

Extensive conversation exists surrounding the role that academic advisors play in the lives of students. Smith (2002) stated that students in his study equated the purpose of academic advisors to identifying courses for degree completion and conveying university policy and procedures. At times, students may not truly understand the roles that academic advisors are meant to play, and some may limit those roles by perceiving them as an extension of their experiences with high school counselor appointments. The role of an academic advisor in a higher education setting is truly impactful in helping students achieve their goals.

Academic advisors are credited with building environments that cultivate repeated interactions to foster student success by encouraging students to seek academic assistance when needed (Amador & Amador, 2014). Creating this environment involves building relationships around trust, respect, and understanding. Such relationships allow advisors to play an essential role for students by helping them to find on-campus resources, by creating plans for academic success, and by providing mentoring during their journey towards degree completion. Academic advising approaches play an important role in allowing advisors to develop these meaningful, trusting relationships with students. Regardless of which advising method an advisor chooses to use, Anderson et al. (2014) stated that the approach must align with student expectations of advising, whether proactive, prescriptive, or developmental. Student satisfaction is dependent on this fact.

There are many different approaches and strategies used to advise students. For the purpose of this literature review, three main approaches will be identified to continue the
conversation about the strategies used by academic advisors to engage with students. There are many other approaches to academic advising, but based on a review of existing literature, the researcher has identified that a number of these approaches were iterations or evolutions from the three strategies listed below. Most recently, Huggett (2004) identified six different approaches commonly used in conjunction with academic advising. These include, prescriptive, developmental, collaborative, integrative, intrusive/proactive, and praxis. The researcher believes that the specific core components of any advising approach can be shared amongst the following three approaches: prescriptive advising, proactive advising, and developmental advising. Many advising approaches were developed after these three and share a number of similarities. These strategies are still being discussed within the academic advising literature. There are three central approaches to academic advising:

1. **Proactive advising model**: This academic advising approach was formerly known as intrusive advising and aims to reduce student attrition due to academic failure (Varney, 2007). In this approach, advisors proactively engage with the student to better support their academic journey.

2. **Prescriptive advising approach**: Advising is prescriptive in nature because the academic advising practitioner is giving information in an authoritative manner (Walters, 2016). The prescriptive advising approach is centered around the advisor prescribing a course plan in order to help the student take the correct courses and limits the interaction to only addressing that specific purpose (Harris, 2018).

3. **Developmental Advising Approach**: This approach supports student understanding of what college is about with a focus on the reasons why majors or career pathways are
selected. This style of advising is designed to help educate the whole student and has a focus on student growth beyond cognitive factors (He & Hutson, 2016).

**Proactive Advising Strategy**

As stated by Varney (2007), supporting the higher education journey goes well beyond course selection, as advisors utilizing this approach are also looking at the holistic aspects of supporting students identified as being high risk (Walters, 2016). When implemented strategically, proactive advising has been credited with helping advising outreach for at-risk and probationary students, which has led those cohorts to have increased academic success. In the Abelman and Molina (2000) research study, there was a direct correlation between GPA increase and retention at the university when the proactive advising strategy was employed (Schwebel, Walburn, Klyce, & Jerrolds, 2012).

**Prescriptive Advising Strategy**

The prescriptive advising approach was developed in the early 1970s after an article was published by Burns B. Crookston and Terry O’Banion in which they shared their views on how advising should be conducted (Huggett, 2004). The idea behind prescriptive advising is exactly as it sounds, it is prescriptive in nature because the academic advising practitioner is giving information in an authoritative manner (Walters, 2016). The prescriptive advising approach is centered around the advisor prescribing a course plan in order to help the student take the correct courses and limits the interaction to only addressing that specific purpose (Harris, 2018). This approach deemphasizes the personal information about a student’s background and focuses on course selection and institutional policies (Amador & Amador, 2014).

The prescriptive advising approach may seem commonplace to students because this approach meets their expectations of the role that advisors play. Prescriptive advising is also
important because it provides concrete guidance. Students often seek this type of expertise for reassurance and confidence to proceed with the information that they are receiving (He & Hutson, 2016). Advisors that use the prescriptive advising approach are seen as having expertise with curriculum information, university policy, and procedure. The prescriptive advising approach allows for essential information, such as course planning and graduation requirements, to be concisely conveyed (Teasley & Buchanan, 2013).

**Developmental Advising Strategy**

Grites (2013) stated that developmental academic advising is one of the most fundamental and comprehensive approaches to academic advising. According to Huggett (2004), Crookston (1994) expands upon the characteristics within the prescriptive advising approach by developing an approach that incorporates aspects of student development theory to define the developmental advising approach. This approach supports student understanding of what college is all about with a focus on the reasons why majors or career pathways are selected. This style of advising is designed to help educate the whole student and has a focus on student growth beyond academic achievement (He & Hutson, 2016).

This approach is particularly important because it allows for academic advisors to gain a better understanding of the student’s holistic development regarding their mindsets, motivations, and understanding of their academic pathway (He & Hutson, 2016). In this approach, advisors use a developmental process with students to encourage independence. Advisors work closely with students to teach them how to build their skill sets in navigating university systems and how to take advantage of co-curricular resources. By utilizing these developmental advising methods, academic advisors are able to make the academic advising process more meaningful for the student (Grites, 2013).
Developmental advising may seem very different to students who are accustomed to a prescriptive advising environment, such as in high school. For some students this may be uncomfortable at first and they may need time to acclimate during the relationship building process with the advisor. However, developmental advising may not be appropriate for all students. It is important for advisors to focus on meeting student expectations regardless of the advisor’s preferred approach (Anderson, Motto, & Bourdeaux, 2014).

**The Unique Role of Honors Platforms**

In this literature review, the term “honors platform” will include both departmental “honors programs” as well as institutional “honors colleges.” Webster (2019) defines platform as “a declaration of principles onto which a group of persons stands.” Using the term platform best encapsulates what honors programs and colleges have been attempting to do for their high-ability students. These programs provide a space in which their students are allowed to stand and acquire knowledge that goes beyond the basics, seek out learning opportunities, and receive the support to flourish both personally and academically (Bowman & Culver, 2018; Hause, 2017; Huggett, 2004).

**The History of Honors Platforms**

Frank Aydelotte is credited with establishing what is now known as an honors education. He “established a program of honors seminars and student concentrations at Swarthmore that brought the college into the first rank of American colleges” (Institute for Advanced Study, 2019). The pedagogical intent of an honors platform may differ by institution (Miller & Dumford, 2018), but the underlying premise is around providing a liberal arts education with additional learning opportunities for high-achieving, academically minded students to enhance their undergraduate experience (Wawrzynski, Madden, & Jensen, 2012).
What Makes an Honors Platform Different?

Honors students engage in personal and professional growth through both academic curriculum and experiential learning. However, there is still minimal research regarding the student experience of honors college participants (Clark, Schwitzer, Paredes, & Grothaus, 2018). Honors colleges are also known for building a sense of community amongst their students, staff, and faculty. Scott and Frana (2008) described the honors college learning environment as a place where both students and faculty are able to practice scholarship and citizenship together.

Students eligible for the honors colleges are typically attracted by the opportunity to connect with faculty, challenging curriculum, participation in experiential learning opportunities, and earning additional scholarships. The honors curriculum offers an integrative approach to learning through interdisciplinary courses that emphasize student-centered learning approaches (Scott & Frana, 2008).

Zubizarreta (2019) stated that honors program curriculums offer students value-added opportunities to experience critical thinking and integrative learning all while contributing to life-long growth. University administrators have seen honors colleges as being dedicated to exclusively serving high-ability students’ needs while also helping to raise admission profiles (Clauss, 2011). Students accepted into an honors college typically have high GPAs and standardized test scores. Kaczvinsky (2007) stated that in the competitive landscape of higher education, universities invest in honors programs to recruit high ability students to attend their institution as an inexpensive alternative to expensive private institutions. Their standardized test scores and high school GPAs all contribute to their relevant qualifications to enter into an honors college program and persist through their university curriculum.
Challenges for Honors Students

In spite of their academic ability, honors students still run into familiar challenges when compared to their non-honors peers while transitioning to college from high school (Walsh, 2010). Campbell and Fuqua (2008) found that honors college retention and completion rates are very poor and that less than 20 percent of students attending the institution within their study completed their honors college requirements. It is important to identify factors that contribute to student persistence in honors college programs. Honors colleges play a critical role in recruiting high-ability students, attracting institutional beneficiaries, and raising the overall profile of their institutions (Clauss, 2011).

As stated, these students are high achieving and academically sound, considering their GPA and standardized test credentials when entering college. Honors college students represent a diverse group of majors, social and cultural backgrounds, and specialized needs within the context of their institution (VanDieren, 2018; Walsh, 2010). Limited research exists when examining retention and completion characteristics of successful honors students. The majority of studies that focus on honors students tend to highlight recruitment and selection and do not attempt to not discuss less measurable items such as honors curriculum, co-curricular requirements, or academic advising (VanDieren, 2018).

Aside from the existing difficulties honors programs face with respect to retention and persistence, honors students face many challenges. Honors students have unique needs beyond learning how to navigate the institutional roadmaps. Honors college students still need support on how to navigate honors college curriculums and guidance on the best pathway to reach academic and professional goals (Hause, 2017). To truly understand the existing challenges and barriers, it is important to examine the factors that contribute to a student's ability to achieve or
underachieve at the university level. Circumstantial challenges of being a college student include managing personal relationships, employment, transitioning family roles, and mental/physical health concerns. All of these can impact a student’s ability to be successful (Walsh, 2010).

**Challenges for Honors Platforms and Academic Advising**

There are many concerns in higher education regarding the sustainability of the current academic advising infrastructure. Faculty have expressed concerns about the role institutions play in achieving sustainable futures and addressing financial barriers, and so it is important for higher education institutions to be models of sustainability (Wright & Horst, 2013). Huggett (2004) stated that honors leadership faces serious fiscal realities that result in their university administrators expecting them to do more while providing academic advising services but with less fiscal support.

Honors colleges deal with growing student populations and increasing university pressures that place higher expectations on retention and completion rates. Academic advising within an honors setting plays a large role in helping to address the issues that concern student persistence and program completion (VanDieren, 2018). A number of factors are in play when considering why students in an honors college have difficulty. Hause (2017) stated that honors students have different needs from others on campus and need advisors to provide detailed plans helping them to persist through the academic curriculum. Unique honors student needs include particular learning preferences and very specific career ambitions.
Academic Advising within an Honors Platform

Honors college students use a systematic approach when investigating academic courses, academic majors, and career decisions. Upon coming to campus, students see academic advisors as resources for helping them with their specialized needs as they pertain to program requirements, course selection, and scheduling (Johnson, Walther, & Medley, 2018). It is this process that makes advisement of course selection a paramount process in the work of an academic advisor. In the Johnson et al.’s (2018) study, advisors were surveyed to better understand their experiences advising honors students versus non-honors students. Advisors noticed that they spent more time working with each student due to the intensity and in-depth nature of their conversations with honors students.

The VanDieren and Morris (2016) article highlighted the Comprehensive Honors Advising and Mentoring Plan called CHAMP to create-time effective, holistic academic advising resources to better address honors students’ needs when seeking advisement. The results of the Johnson et al. (2018) study also highlighted the important components of understanding honors students and their specialized needs. The study involved interviewing academic advisors and asking them about their experience when advising honors students. These interviews yielded insight as to why students come in to see advisors beyond discussing policies and procedures, honors requirements, and course selection. Honors students seek to have personalized one-on-one attention from their academic advisor. The desire is for the advisor to be the “one stop shop” for all of their academic and professional needs.

Hause (2017) goes on to advocate for attention to be placed on pairing key features of academic curriculum with honors academic advising. Why not bring a student-centered approach from the classroom into the advising approaches used by academic advisors? The same personal
connection and intellectual stimulation taking place in the classroom should also be emphasized by the work of advisors to provide individualized academic advising (Alger, 2015).

Honors student involvement in these programs promotes both persistence and academic achievement. The most notable aspect of the Bowman and Culver study was that participation by the students in honors platforms “predicted greater college GPA, retention, [and] on-time graduation at less competitive schools” (Bowman & Culver, 2018, p. 272).

The researchers suggest the need for “further discussion in both research and practice” (Johnson et al., 2018, p. 117). Advisement on course selection is paramount to the work of academic advisors, but it is the strategic use of academic advising approaches which can be seen as investments in both the present and future of the student's involvement within the honors platform (Johnson et al., 2018). In summary, honors platforms are designed around supporting learning through an interdisciplinary approach, encouraging student’s mastery of uncertainty and ambiguity through experiential learning and independent studies, and respecting diversity while building a sense of community through student, faculty, and staff interactions.

**Demonstrated Need for Improved Efficiency in Academic Advising**

The literature confirms existing challenges in academic advising including concern for sustainability and a need for continued infrastructure development to foster improved efficiency (Wright & Horst, 2013). Honors platforms face increasing expectations from administration while being challenged with less fiscal support. Student populations continue to grow, making retention and completion rates more challenging to achieve. Fortunately, honors colleges are poised to deliver individualized in-depth academic advising services to meet the needs of their high achieving student population. Honors platforms are attractive to high-ability students who raise the overall admission profile of their institution with high GPAs and standardized test
scores. This is important in the competitive landscape of higher education. This portion of the literature review supports the need for more efficient and strategic utilization of academic advisors. By performing a gap analysis specifically for honors platforms, the researcher can then begin to develop a tool that will help improve academic advisor efficiency.

Section 2: Human Performance Technology

Human Performance Technology Introduction

The founders of HPT learned that there is power in observation, empirical measurable evidence, and principals of reasoning (Pershing, Abaci, & Symonette, 2016). Literature review findings confirm that Human Performance Technology (HPT) is a framework for analyzing processes and developing low-cost measures for performance improvement (Kang & Molenda, 2018; Carliner, 2013; Kang, 2016; Wells, Stanley, & Martin, 2014). There is a heavy focus on gap analysis in the HPT model because the quality of the analysis phase is critical to every subsequent phase in the process (Marker, Villachica, Stepich, Allen, & Stanton, 2014). HPT is a systematic inquiry model which includes the following steps: performance analysis, intervention selection/design/implementation, and evaluation (Kirkpatrick, 2017; Dessinger, Moseley, & VanTiem, 2012).

Organizational and environmental components are part of the performance analysis which provides a global view of the system to identify performance gaps within the larger structure/environment (Dessinger et al., 2012; Wells et al., 2014). The identification of specific performance gaps using HPT leads to the design of interventions which focus on behavioral improvement. An example of this would be performance support tools such as job aids that help workers in the field to better perform required tasks. Askar (2018) found that electronic job aids allowed for improved work efficiency within the environment.
Sources for literature pertaining to HPT research are limited. The International Society for Performance Improvement is one of the largest sources of HPT research. The Association for Educational Communication and Technology (AECT) is a professional organization for instructional technologists, instructors, and researchers, and has also provided high quality research on HPT.

HPT has multiple definitions, creating a challenge for practitioners and researchers to illustrate and validate the HPT model (Kang & Molenda, 2018; Abaci & Pershing, 2017). As a result of the wide conceptualization of HPT, the model is simultaneously praised and criticized for lacking a rigid structure (Pershing et al., 2016). Although the HPT model yields concrete data regarding existing gaps, the overall process can be more subjective than other performance improvement models. Existing criticism includes the need for improved understanding of the field of HPT in order to dispel myths and opinions that are often promoted as part of performance improvement (Abaci & Pershing, 2017).

One of the reasons why research specific to HPT is lacking is because over the years, HPT has been dissected and parts of the model have been borrowed and reengineered in various settings, distorting the original process but yielding many new useful versions (Pershing et al., 2016; Kang & Molenda, 2018). Ultimately, this application of HPT in various settings provided a better understanding of the HPT process. Although HPT has a documented history of use in business settings, the literature reveals that it can also be used well within higher education and specifically within individual departments. The use of HPT within higher education settings has been shown to assess department efficiency and performance and promote useful interventions to improve performance gaps (Hemalatha et al., 2014; Wells et al., 2014).
History of Human Performance Technology

In Peter Dean's article (1998), Thomas Gilbert is credited with being labeled the “father of performance technology” because he devoted his life's work to understanding the principles behind performance through his vantage point as an interdisciplinary philosopher. During his career, Gilbert developed a number of performance improvement models such as Behavioral Engineering Model (BEM), worthy performance, Performance Improvement Potential (PIP) performance audits, and the ACORN test. The ACORN test is named so because it evaluates improvement projects by labeling the accomplishments, control, objective, reconciliation, and numbers to allow teams to clarify the mission of an institution at the policy level (Dean, 1998). The BEM model was Gilbert's diagnostic tool for conducting a cause analysis. This cause analysis model separated performance problems into two categories: individuals and environments (Ross & Stefaniak, 2019). BEM is a process improvement model examining what elements contribute to the behavioral performance of the individual using three steps:

1. Properly identify the desired behavior;
2. Measure ideal performance;
3. Identify strategies for performance improvement (Ross & Stefaniak, 2019).

Over time, Gilbert continued to evolve these three steps which contributed to the foundation for the Human Performance Technology model. The HPT model is scientifically proven to increase an individuals’ ability to amplify their output. Gilbert used a number of methods during his work in industry. He credited critical observation of environmental barriers as being a core component of enabling individuals to perform at a maximum level (Wilmoth, Prigmore, & Bray, 2014). Gilbert’s methodologies were perfected into a set of tools which
helped a number of industries in technology and business sectors convert potential into capital (Gilbert, 2019).

**Conceptual Framework Behind HPT**

For the remainder of this literature review, the acronym HPT will stand for Performance Improvement/Human Performance Technology. The researcher will provide a summary of the research conducted on both Performance Improvement as well as Human Performance Technology. The terms will be synonymous and do not require any further delineation within this literature review.

HPT is a systematic process of discovering and analyzing an essential human performance gap (Kang & Molenda, 2018). It is Gilbert's ideas and models about human performance competencies that laid the conceptual framework for the development of the Human Performance Improvement/Human Performance Technology (HPI/HPT) model. Dean (1998) stated that there are three primary principles when understanding Gilbert's perspective on scientific theory; "the importance of parsimony: don't use grand complexities to explain something that can simply be said, elegance - pieces and parts of a good theory should fit nicely together, and usefulness - a good theory should have utility - if not in the real world at least in helping science advance" (Gilbert & Gilbert, 1991). Performance technology provides a holistic approach to understanding human potential by fine-tuning performance drivers that can contribute towards the development of human capital (Surry & Stanfield, 2008).

Wilmoth et al. (2014) stated that Joe Harless was a central figure who is credited as a pioneer in developing the conceptual framework of HPT because of his work, which expanded upon Gilbert's research. Harless championed understanding the root cause through a comprehensive front-end analysis to arrive at an appropriate solution (Wilmoth et al., 2014).
HPT professionals advocate using a combination of both qualitative and quantitative data in combination with observation to carefully examine the relationships and activities that humans take part in which may require performance improvement (Klein, 2002). In using both qualitative and quantitative methods to gather data, HPT researchers must carefully design interventions that look at multiple perspectives. It is precisely why Harless went on to propose that interventions or solutions must be designed from a cost-effective approach that serves a business focus (Wilmoth et al., 2014).

From Harless and his contributions to the field of HPT, two points remain appropriate in consideration for this study. One is that Harless emphasizes front-end analysis as essential to understanding the cause of a problem and how these causes, once identified, can lead to driving an appropriate solution (Wilmoth et al., 2014). The second point is the notion of partnership. Harless prioritizes having a partnership between the stakeholders during all phases of analysis as crucial when seeking understanding of environmental issues, economy, and elements of human nature (Pershing et al., 2016).

Pershing, Abaci, and Symonette (2016) asserted that the systematic application of theories is the primary reason why Human Performance adds the word Technology to support the principles that address the scientific methods within the model. HPT professionals are able to build upon the foundation laid by Gilbert, Harless, behavioral scientists such as Richard Skinner, and the field of instructional design (Dean, 1998). Within HPT, practitioners must develop a blueprint that focuses on solving problems, enlightens the participative nature of human interaction, and utilizes systematic inquiry processes for holistic solutions. Creating these blueprints relies upon empirical research to improve human performance or reach desired performance through various scientific approaches and evidence (Klein, 2002).
Professional Organization Structure Model

The International Society of Performance Improvement (ISPI) is a non-profit professional association that advocates for the promotion of performance improvement professionals and the utilization of performance improvement in the workplace. The ISPI is home to one of the largest publications promoting performance improvement/HPT. The organization also created 10 standards for performance improvement that can be applied to any organization in order to create successful solutions for performance challenges or opportunities (ISPI, 2019a). The standards address the following areas:

1. Focus on Results or Outcomes
2. Take a Systematic Review
3. Adding Value
4. Work in Partnership with Clients and Stakeholders
5. Determine Need or Opportunity
6. Determine Cause
7. Design Solutions Including Implementation and Evaluation
8. Ensure Solution Conformity and Feasibility
9. Implement Solutions
10. Evaluate Results and Impact

These standards provide a guide for HPT professionals when considering implementation process models. The standards promote a multi-perspective view, addressing the need for practitioners to understand the situation from environmental, system, and individual points of view. Regardless of the environment, these standards can be applied in a number of workplace or
institutional situations aimed at addressing or identifying opportunities, problems, and solutions. Even with this understanding, Wilmoth et al. (2014) stated that there is no single model that can be applied universally.

Figure 1. Performance Improvement Using the HPT Model (Van Tiem et al., 2012)

**Phase 1: Organizational and Environmental Analysis**

Performance analysis is two pronged and begins with organizational analysis, including vision, mission, values, goals, strategies, and critical issues. The second prong of analysis is environmental analysis which considers world, workplace, work, and the worker. World entails culture, society, and social responsibility. Workplace includes organization, resources, tools,
stakeholders, and competition. Analysis of work includes workflow, procedure, responsibilities, and ergonomics. Lastly, the worker analysis involves knowledge, skill, capacity, motivation, and expectations (Dessinger et al., 2012). Organizational analysis yields the desired performance. Environmental analysis yields data on the actual performance. Using these two disparate data sets, a gap analysis can be performed.

The analysis is a central component in the Performance Improvement / HPT model because it places an emphasis on performance needs and opportunities (Dessinger et al., 2012). The science of HPT yields data via performance analysis and from this, the HPT team is able to understand what is needed. The HPT framework validates the findings. The model emphasizes an understanding of the vision, mission, critical issues, goals, strategies, and values of the organization (ISPI, 2019b). HPT is known for using a systematic approach to understand how to help individuals as part of a group and leverage their abilities within an organization to perform more effectively. Understanding the environment allows the researcher to better assess the workplace factors that are impacting the actual performance of the individual. The results from both the organizational and environmental analysis are synthesized and analyzed during the gap analysis/cause analysis.

**Phase 2: Gap Analysis/Cause Analysis**

Gap analysis is the process of determining the gap between the desired performance and the actual performance. Once the gap analysis is complete, the cause analysis can begin. Cause analysis involves both environmental factors and individual factors. Environmental factors include data, feedback, environment supports/resources/tools, consequences, incentives, and rewards. Individual factors include skills/knowledge, individual capacity, motivation and expectations (Dessinger et al., 2012).
HPT emphasizes analysis to reveal causes of problems within the system or organization at the specific level at which the problem occurs (ISPI, 2019b). Conducting an HPT analysis allows organizations to evaluate the current level of performance and identify the desired performance level (Hemalatha et al., 2014). Having a clear concept of the desired performance (the goal) is needed to accurately identify and address the existing performance gap (the problem). The cause analysis will help identify both the environmental and individual factors resulting in gaps that ultimately impact individual performance. Dessinger et al. (2012) stated that conducting an organizational analysis as well as an environmental, gap, and cause analysis are all crucial in the performance analysis process. These analysis areas offer specific insights as to the root cause of the performance gap issue. In this manner, the HPT model focuses on achieving measurable results from a data-driven process.

**Phase 3: Intervention Selection, Design and Development**

The intervention selection, design, and development phase can be sorted into categories of interventions and “business cases” or the organization’s ability to respond to and sustain the intervention. Interventions may include but are not limited to learning, performance support, job analysis/work design, personal development, human resource development, organizational communication, organizational design/development, and financial systems (see Figure 1). From a business perspective, interventions to consider include leadership commitment, feasibility, and sustainability. After the intervention is selected and prepared, then HPT moves forward to the intervention, implementation, and maintenance phase (Dessinger et al., 2012).

Identifying performance gaps is an essential part of evaluating an organization's performance metrics. Without a proper evaluation of performance gaps, it is impossible to define appropriate solutions (Kang, 2017). Once both the current level of performance and the desired
behavior/outcome have been identified, then the design of an intervention can begin. The purpose of the intervention is to address the gap in performance. Thus, by using the results of the performance analysis, both needs and opportunities will present themselves to drive the selection, design, and development of an appropriate intervention (Marker et al., 2014).

**Phase 4: Intervention Implementation and Maintenance**

Implementation and maintenance of the desired intervention may be achieved through various techniques, such as partnering, networking, alliance building, process consulting, employee development, communication, and project management (Dessinger et al., 2012). It is important for practitioners of HPT to take into consideration the end user’s experience with the intervention. Practitioners must create an intervention and implementation plan while considering the client’s ability to maintain such a solution (Marker et al., 2014). This intervention process might include partnering with others within the organization or hiring a private consultant to provide an objective viewpoint (Kirkpatrick, 2017).

**Phase 5: Evaluation**

The final phase, evaluation, consists of four categories: formative, summative, confirmative, and meta evaluation/validation (Kirkpatrick, 2017). Formative evaluation is considered level 0 and incorporates performance analysis, selection/design/development, implementation, and maintenance. Formative evaluation is the input-process-output evaluation. Levels 1-2 evaluations are summative and include immediate evaluations of reactions, knowledge/skills/attitude changes and application. Confirmative evaluation occurs in levels 3-5 and is concerned with sustainability, including effectiveness, efficiency, impact, and value of the intervention. The final level of evaluation is meta evaluation or validation of the intervention including formative, summative, confirmative inputs-processes-outputs, success stories, and
lessons learned (Dessinger et al., 2012). As illustrated in Figure 1 above, the evaluation phase takes place throughout the entire HPT process, from beginning to end. The meta evaluation/validation phase can only occur after the interventions have been implemented for a period of time. Verifying that the desired results are being achieved is essential.

**Findings: The HPT Model is Proven to Work**

This portion of the literature review confirms that the HPT model is scientifically proven to increase individuals’ ability to amplify their output. The HPT model provides a systematic workflow for organizing observations and analysis of desired performance outcomes. This allows for a clear interpretation of the root cause of the performance problem. The HPT approach offers solutions and opportunities to address performance issues through a detailed performance analysis that includes organizational components, environmental components, performance components, and desired/ actual work analysis.

Utilizing such a model strengthens decisions and interventions to address the gaps identified through the use of HPT assessment. Training is not necessarily the primary intervention, although solutions may include training. It is more important to the HPT researcher to co-create opportunities/solutions that address the needs of all stakeholders and users based on the data collected within the organizational and environmental analysis. It is this level of detail that helps to validate the performance analysis process of identifying performance gaps. The perpetual phases of analysis inherent in the HPT model ultimately provide validation of the intervention(s) designed to achieve the desired performance.

The HPT model is straightforward and versatile. It is meant to fit into most types of business and organizational structures (Hemalatha et al., 2014). Existing literature confirms that HPT is appropriate for use within a higher education setting, such as an academic advising
honors platform. Utilizing HPT can help to improve and influence community and environmental changes that in turn contribute towards student performance and engagement (Esmail & Ransom, 2016). Student performance indicators such as persistence and retention are a top priority for higher education institutions who are under pressure to improve performance with less financial support. Academic advisors are a key component to addressing the issues of student performance, engagement, persistence and retention. Kang (2017) urged professionals to consider the importance of utilizing the ISPI HPT model as a framework within both research and consultations. HPT provides an opportunity for academic advising departments to perform a gap analysis which will yield validated interventions to address these issues.

Section 3: Chatbot Technology

Chatbot Technology Introduction

With the rapid acceleration in technological advances, much of our communication occurs through digital technology rather than in person (Yau, Zhang, & Chen, 2015). Chatting with friends and family online via web or mobile applications or using Amazon Alexa through a digital speaker interface has become a natural and familiar communication process for many people with access to the internet (Jain, Kumar, Kota, & Patel, 2018). Chatbots are computer applications designed to be conversational agents that respond to user inquiries by mimicking human natural language responses (Allison, 2012; Araujo, 2018; Chan, Lee, Lo, & Lui, 2018; Przegalinska et al., 2019; Radziwill & Benton, 2017).

The literature available on chatbot technology suggests it is a useful tool in a number of different settings, including but not limited to business, healthcare, and education (Allison, 2012; Fryer, Ainley, Thompson, Gibson, & Sherlock, 2017; Nwankwo, 2018; Radziwill & Benton, 2017). One key chatbot feature is the ability to simulate human conversation through natural
language (Braun, Mendez, Matthes, & Langen, 2017). That simulation allows for an organization to communicate with its intended users to address their needs. Users may include population groups such as customers, patients, or students. Chatbots are useful to address various customer service, learning, and informational needs (Almansor & Hussain, 2019; Fryer et al., 2017).

Existing literature focuses largely on what constitutes a success or a failure for a chatbot. The success of a chatbot application is largely determined by the chatbot’s ability to communicate the desired information in a correct and efficient manner (Carayannopoulos, 2018; Jain et al., 2018; Mimoun, Poncin, & Garnier, 2012; Ni, Lu, Liu, & Liu, 2017; Zamora, 2017). This literature review revealed a significant amount of variability as to what constitutes successful implementation of a chatbot. The number one criticism of chatbots is failing to “listen to the customer,” as in failing to give the desired response (Jain et al., 2018; Przegalinska et al., 2019; Radziwill & Benton, 2017). Chatbots are still a relatively new technology, and because of this, more research is needed on proper utilization and implementation within various settings.

During the course of this literature review, the researcher was unable to identify theories or pedagogies relating to chatbots. There is research available on chatbot design and user perceptions, but little research on the assessment of chatbot efficiency (Radziwill & Benton, 2017). There are varying opinions on how to measure chatbot efficiency and success (Mimoun et al., 2012; Przegalinska et al., 2019).

The area of research surrounding chatbots is important. Building off of the data-driven process of the HPT model, chatbot applications appear as viable resources for investigation because of their deployment ability, scalability, and efficiency for information sharing (Przegalinska et al., 2019). These conversational agents are an effective tool and have been used as aids to better serve users with in-time support of navigating large volumes of information.
(Carayannopoulos, 2018). The researcher believes it is important for higher education institutions to be aware of the technologies that may afford an opportunity to leverage their vast resources in a more effective way to aid students, faculty, staff, and the surrounding community. Gaining a crucial understanding of how chatbot applications can impact an organization can help to guide the future of chatbot applications within higher education institutions. To better understand the key components of chatbot applications, it is important to have a historical view of the development of these applications and an understanding of the structures that guide implementation.

**The Historical Context of Chatbot Applications**

Chatbots are one of the few technologies created in the 1960s that have still not reached their full potential since their initial conception. Born out of the MIT artificial intelligence lab in 1966, ELIZA was the world’s first chatbot utilizing natural language that mimics human communication (Przegalinska et al., 2019; Radziwill & Benton, 2017; Weizenbaum, 1966). Just like any computer software, chatbots rely on input. The term “natural language” refers to the use of software technology for analyzing, understanding, and interacting with humans in their natural language without the need to write code (Berger, Ebner, & Ebner, 2019; Latorre-Navarro, 2014; Przegalinska et al., 2019).

What we know about chatbots and the use of AI was predominantly established by Artificial Linguistic Internet Computer and Entity (ALICE) in 1995 (Wallace, 2003). ALICE was the first chatbot to have a true conversation with a human (Kerlyl, Hall, & Bull, 2006). From there, advances in natural language and AI have helped to establish the foundations for utilizing chatbots within a number of areas such as business, industry, and education (Allison, 2012; Berger et al., 2019; Nawankwo, 2018). Chatbots are an evolution of computer software in that
they present a cost-effective medium to addressing a need. However, chatbots also present challenges. Research also points to potential harm from chatbots being used as part of social engineering to dispense false information or abuse (Radziwill & Benton, 2017). A clear understanding is needed regarding how these applications are designed and implemented.

**Chatbot Architectures and Approaches**

Chatbot applications are a form of intelligent agents that engage humans in task-oriented or informal conversation in an interactive way (Srivastava, 2018). Chatbots are a computer or web application that convincingly simulate how a human would behave as a conversational partner by processing natural-language text or voice input from a user and generating smart and relative responses (Georgescu, 2018; Almansor & Hussain, 2019).

All chatbots operate as conversational interfaces by using three primary structures in their architecture: client-side user interface, back-end information processing, and a natural-language platform for artificial intelligence support (Berger et al., 2019). These architectures help to support the complex mechanisms that integrate both natural language modeling and computational algorithms needed for chatbot software to communicate with users (Roca, Sancho, García, & Alesanco, 2019). Chatbots can benefit from the incorporation of these elements to better engage users when navigating complex or large amounts of information.

Chatbot system architecture requires an effective approach when building automatic conversation agents, providing relevant contextual data to power chatbot responses (Almansor & Hussain, 2019; Radziwill & Benton, 2017). Chatbots are governed by rules programmed into the application, and these rules dictate the chatbot’s ability to offer appropriate resources. There are three categories of chatbot approaches which include: information retrieval, task-oriented dialogue systems, and non-task-oriented dialogue systems (Almansor & Hussain, 2019; Leuski
& Traum, 2011). Within the first dialogue structure, there is a supervised approach and an unsupervised approach that supports how the application will respond to user inquiries (Yan, Duan, Bao, Chen, Zhou, Li, & Zhou, 2016).

The task-oriented system is designed to help users complete a specific task. This is in contrast to the non-task-oriented system which is designed to aid the user in receiving assistance in answering a question within a relevant set of responses (Almansor & Hussain, 2019). An example of the task-oriented dialogue system would be setting an alarm using your Amazon Alexa device. In this example, the conversational agent is able to perform a specific task for the user. A non-task-oriented dialogue process provides relevant responses to inquiries, but does not complete a task for the user. An example of this could be a chatbot on Facebook or a built-in Skype bot giving a user a business’s hours of operation. The last approach is considered a retrieval-based structure for chatbot design. This structure enables the chatbot application to answer questions based on the pre-matched collection of responses relevant to a particular topic within a knowledge database (Leuski & Traum, 2011).

**Chatbot Implementation and Datasets**

Chatbots usually rely on other applications that support the chatbot in acquiring and disseminating information (Berger et al., 2018). The goal of a good data set is to support improved user and chatbot interactions. For example, the Kanazawa Institute of Technology in Japan developed a chatbot advising tool which operated from a large dataset containing over 1,000,000 records of former graduates, including their profile, recorded thoughts, activities, and histories (Fukuda, Izumiya, Takashima, Takechi, & Araki, 2018). The potential capacity for chatbot databases is impressive, as evidenced in this example. However, building out an extensive knowledge database to support a chatbot application implementation is a time-
consuming and difficult process (Arsovski, Osipyan, Oladele, & Cheok, 2019). The process of building a chatbot and designing the associated database requires machine learning. Machine learning is the process of feeding knowledge into the application and into the database while allowing for that information to be delivered back to the user via the natural language process (Radziwill & Benton, 2017).

Users must operate with the understanding that no chatbot will be perfect and that all users must employ a critical lens when assessing the results received from the chatbot. Abdul-Kader and Woods (2015) stated that constructing the ideal chatbot application is a difficult process due to the necessity of training and implementing a large and comprehensive data set to enable users to retrieve reasonable responses. Users can search for information by keywords as well as natural language using complete sentences. This convenience is an advantage of a chatbot versus using a website or search engine (Kim, Ruiz, & Peterson, 2006).

**Chatbot Development in Education**

Carayannopoulos (2017) highlighted that chatbots are often used as a communication tool which can be useful in helping students manage information overload and help them to feel more personally connected to the instructor. There are several exciting applications of chatbots in higher education and advising. One example was the EASElective chatbot designed at the Open University of Hong Kong. EASElective provides universal and 24-hour access to advising services (Chan, Lee, Lo, & Lui, 2018). In addition to official university information, EASElective is able to provide peer opinions and recommendations for course selection.

Another example found within education is a chatbot application in China that provides real-time virtual reference services online 24/7 and year-round for the Tsinghua University library (Yao, Zhang, & Chen, 2015). The Xiaotu chatbot application offers an interesting
perspective on chatbot implementation in higher education. Xiaotu’s ability for natural language communication in Chinese and its ability to provide expert answers to users helps structure the narrative surrounding the usefulness of a chatbot in higher education. This directly relates to chatbot implementation in academic advising/higher education by demonstrating how it is a useful tool which can offer cost-saving measures.

The Coniam (2008) article discussed the relevance of chatbots in language acquisition and their potential to aid learners in receiving conversational practice through the use of computer-assisted language learning chatbots. Chatbots are a valuable tool for English as a second language instruction because they offer the opportunity for users to engage in a conversation similar to human communication. Having conversational partners is one of the most requested elements when learning a language (Coniam, 2008). Chatbots can be a useful tool to fill this need, but conversation with chatbots is still limited because they are only capable of interactions that are programmed within their database. Allison (2012) emphasized the importance of AI and the use of Natural Language Interaction (NLI) in chatbot design in order to provide responses that are more sensitive to the intent of the original question.

There are many different purposes for chatbots: some chatbots are designed for informational and educational purposes, while others are made for non-educational purposes, such as social interaction - including virtual social companions and hosts (Rubin, Chen, and Thorimbert, 2010). Rubin et al. (2010) examined the development of chatbot applications and their usage in library systems. Allison (2012) asserted that libraries are looking for new ways to engage users who are consistently demanding more than static websites and who have higher and higher expectations of library services. Considering the ability of chatbots to handle known repetitive searches and provide general library reference task assistance, such as helping users
with exploratory searches, chatbots position themselves as an ideal resource for information seekers.

**What Constitutes Chatbot Success?**

Existing literature attests to the fact that chatbots have been increasingly well received and have become a popular form of intelligent agents that take dialogue context into account during conversation (Srivastava, 2018). Chatbots scale nicely, meaning that they are able to address the needs of people at a larger scale than the available human capital (Ni et al., 2017). For organizations unable to afford a large staff, chatbots can be used to triage customers so that only people with higher level needs or questions are directed to the available human employees. Chatbot applications are designed to extend the existing resources of an organization (Dash, McMurtrey, Rebman, & Kar, 2019).

In an educational setting, chatbots and instant messaging have been shown to share the ability to offer quick conversation, general convenience, and ease-of-use which have all been attributed to offering a greater sense of connection between students and faculty (Carayannopoulos, 2018). Chatbots have been shown to encourage students within learning situations such as library research and language acquisition (Allison, 2012; Coniam, 2008; Fryer et al., 2017; Rubin et al., 2010; Yau et al., 2015). Users report that engaging with a chatbot is preferable to browsing multiple websites and helps to manage information overload (Carayannopoulos, 2017; Ghose & Barua, 2013; Kim, Ruiz, & Peterson, 2006). People also enjoy interacting with chatbots that have a little bit of personality and humor (Radziwill & Benton, 2017). Another chatbot strength is the nature of its functionality, which can be run 24/7, unlike most human resources (Chan, Lee, Lo, & Lui, 2018; Georgescu, 2018; Dash et al., 2019).
Chatbots offer personalization features that can facilitate individualized learning. While available information might be the same on a website, a chatbot can provide curated information which is personalized to the user (Jain et al., 2018; Przegalinska et al., 2019). Academic advising chatbots are capable of offering a similar adaptability and personalization to students in a higher education setting (Nwankwo, 2018). Chatbots have to engage the user by providing them information in a way that is presented clearly, concisely, and going beyond multi-page web searches to distill an answer for their question (Carayannopoulos, 2017; Nwankwo, 2018). If it takes more steps to distill information from a chatbot than it would to get the same information when using a search engine on the web, then the chatbot would be considered ineffective. It is the personalization of information provided by an academic advising chatbot that is its utility (Jain et al., 2018; Nwankwo, 2018; Przegalinska et al., 2019).

**What Constitutes Chatbot Failure?**

Equally important as to what constitutes a successful chatbot, the existing literature cites reasons as to what often results in chatbot failure. Poorly constructed chatbots are often cited as being inefficient, making it difficult for the user to obtain the desired information. Overly mechanical interactions are also frustrating to users (Jain et al., 2018). At the beginning of an interaction, chatbots should explain well up front what is included in their capacity, as users spend short amounts of time and often do not return to use chatbots again when the user does not clearly understand what the chatbot is able to do (Nadziwill & Benton, 2017).

Chatbots should be marketed appropriately for their functionality. In other words, chatbots are criticized when they do not do what they are promoted as being able to do. Criticism of chatbots occurs when the chatbot is not programmed with the ability to provide quality conversation beyond the basics (Jain et al., 2018). Despite the fact that users want quality
conversation and a chatbot that has humor and a personality, the literature also reported criticism for an experience referred to as the “uncanny valley” where users were turned off to the chatbot because the chatbot personality seemed too human (Ciechanowski, Przegalinska, Magnuski, & Gloor, 2019).

**Assessment Measures for Chatbots**

Chatbots are primarily assessed via user performance data (Przegalinska et al., 2019). User interpretation of their interactions with the chatbot are an important measure of success or failure (Zamora, 2017). Chatbot performance metrics often revolve around engagement, which is the length of time a user spends engaging with the chatbot application. Certain applications are designed to be quick and efficient, so length of user time would be less important than frequency of use.

Retention rate is another assessment measurement. Retention refers to users frequently returning to use the chatbot. Poor retention rates likely indicate a lack of trust or perceived utility of the chatbot (Przegalinska et al., 2019; Zamora, 2017). Significant retention is typically a positive indicator (Radziwill & Benton, 2017). The following items are necessary to promote trust in a chatbot application: reliability, integrity, confidence, privacy, safety, and objectivity (Przegalinska et al., 2019). A chatbot’s ability to personalize the interaction for each user also promotes user retention and prolongs engagement with the chatbot (Lee & Choi, 2017).

**Interpretation: Chatbot Utility within Higher Education**

There have been a number of chatbots already deployed in industries such as social media, banking, business, and education. Chatbot internet user saturation is on the rise and it is important for organizations to see how such tools can be used as a way to better leverage resources and maximize efficiency (Jain, Kumar, Kota, & Patel, 2018). Chatbots allow for
automation of low-level processes for dispersing information. Utility has been proven for navigating large volumes of content, as seen in both university library and advising settings. Chatbots allow organizations to use human capital in a more strategic manner, focusing work time on complex processes that require human attention. From the available literature, the researcher received guidance on how to properly design a chatbot for success, such as ideal features, methods for implementation, and how to avoid common pitfalls.

**Literature Review Conclusion**

This literature review has explored the relationship between Human Performance Technology (HPT), chatbot applications, and academic advising. The literature confirms existing challenges in academic advising, including concern for sustainability and a need for continued infrastructure development to foster improved efficiency. A need exists for more efficient and strategic utilization of academic advisors. Human performance technology is a tool for assessing and improving environments which can be implemented within academic advising, using chatbot technology as a vehicle to narrow performance gaps. Literature suggests that the current constructs of academic advising can be modified for improved efficiency in terms of delivery of prescriptive academic advising to undergraduate honors college students. Research findings confirm that the HPT model is scientifically proven to increase an individual's ability to amplify their output.

The data captured as a result of a prior honors departmental HPT needs analysis provided insight as to how to best meet honors student advising needs. The researcher created a concept and implemented a plan to provide a more efficient prescriptive academic advising delivery system using a chatbot designed for the department, known as the AVA chatbot. The perpetual phases of analysis inherent in the HPT model were used to validate the chatbot regarding its
ability to achieve the desired performance. The AVA chatbot application aimed to provide low-
level processes for dispersing prescriptive advising information to honors students, which
liberated academic advisors to focus on more complex student needs. This initiative helped move
the department towards the overarching goal to improve student persistence and retention within
higher education.
CHAPTER THREE:
METHODOLOGY

Section 1: Introduction

This study addressed the innovative approach of advising automation by describing the design and development process of an AVA chatbot system, and further evaluating the effectiveness of the system in a higher education setting. This chapter describes the research methodology including participants, research design, study materials, measurement instruments, study procedure, type of data to be collected, and data analysis methods.

Research Questions

1. What are the demographics of students who use the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?
2. How are students using the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?
3. How do students perceive an Advising Virtual Assistant (AVA) chatbot as a tool for answering their academic advising questions?
4. How efficient is the Advising Virtual Assistant (AVA) chatbot at addressing prescriptive academic advising questions?

Participants

The target population included all undergraduate students in the honors college at a research one institution located in southeastern USA. A total of 2,457 active students were engaged in honors advising at this institution at the time of the study. According to VanDieren
(2018) and Walsh (2010), honors students at large represent a diverse group of majors, social and cultural backgrounds, and academic credentials as evidenced by their standardized test scores and grade point averages. Honors college participants have unique and complex needs and also place value in more developmental academic advising interactions (Scott & Frana, 2008). It was appropriate to implement the AVA chatbot for some of the university’s most demanding students who place very high expectations on advising services.

Study participants first received notice of the AVA chatbot's launch via an advising email welcoming students back for the fall 2020 semester. The AVA was housed within a newly created honors portal which is a landing page for students to access their department information. The researcher had initially anticipated that roughly 50% of the 2,457 students enrolled in the honors college might have been interested in engaging with the AVA chatbot, but found that student engagement with the weekly newsletter and other electronic communication was lower due to the COVID-19 pandemic. Both the emails and newsletter were sent to all active students of the honors college and all communication brought attention to the new honors portal. Some advisors put the link to the honors portal in their email signatures so that students would always have access to a link to the portal. Some also put the link to the portal in their out-of-office emails to encourage students to use it as a resource when their assigned advisor was not available. The goal was to place the AVA chatbot where students would naturally go to learn about advising information. Students accessed the honors portal (see Appendix 2) from the honors college website and logged in via a secure password-protected site. Students were encouraged to complete an online survey upon completion of their session with the application. At launch, all 2,457 students had access to the AVA chatbot.
Research Design

Richey and Klein (2007) stated that Design and Development Research (DDR) is “a systematic study of design, development and evaluation processes with the aim of establishing an empirical base for the creation of a product or tool” (p. 1). Design and Development Research guided the approach employed for the structure of data collection, data analysis, and presentation. As a result, the researcher focused his assessment on the AVA intervention tool, specifically on reliability, participant confidence, and participant performance data based on Przegalinska et al.’s (2019) research. Their work stressed the necessity of these items in promoting trust in a successful chatbot implementation.

This study’s research design was structured with an emphasis on the specific aspects of the AVA’s ability to deliver prescriptive advising information. Any intervention or tool must be positioned to alleviate the identified problem as a result of a specific needs analysis (Sahrir, Alias, Ismail, & Osman, 2012). The researcher also placed great emphasis on studying the specific aspects of how AVA participants engaged with the application. The study highlights the design, development, and outcomes learned from participant interaction with and researcher observation of the AVA. Within a natural work setting, DDR guided the researcher in establishing a process in which testing and validation could occur (Richey & Klein, 2007). The AVA was field tested to clearly highlight the benefits and challenges of designing, developing, and implementing chatbot applications. The researcher shared the AVA chatbot conceptual design, pictured in appendix 4, with students and academic advisors. Both groups provided feedback on design elements, overall structure, and utility. The researcher repeated this process
throughout the design and implementation stages. Data obtained contributes to the body of knowledge about chatbot use in academic advising.

Section 2: Design and Development of Advising Virtual Assistant Chatbot

HPT Process: Performance Analysis of Need and Opportunity

The AVA chatbot (see Appendix 3) was created after conducting a performance gap analysis based on the HPT model, which involves a series of processes to identify performance problems and needs, possible causes, interventions, and formative/summative evaluation. The researcher consulted with fellow academic advisors and department leaders about the needs within academic advising and the importance of providing resources to help close performance gaps.

Organizational Analysis

The departmental mission emphasizes the importance of providing transformative educational opportunities to intellectually high-achieving undergraduate students. This is done through interdisciplinary course curriculum, meaningful experiential learning opportunities, and supportive academic advising services. The departmental goal is to improve student retention. Student retention is aided when advisors support students to advance in their academic and professional pursuits.

Environmental Analysis

Prior to launching the AVA, the department had limited resources to allow students to access prescriptive academic advising information without scheduling an appointment with an academic advisor or sending an email to an academic advisor. Students were highly motivated to seek out academic advising resources in an attempt to receive in-time support to assist them towards degree completion.
Desired Performance

Hemalatha et al. (2014) stated that evaluating the current level of performance brings opportunity to enhance the desired performance. Desired performance included:

- Students persistence towards academic completion in an efficient and timely manner
- Students proactively obtain prescriptive academic advising resources independently
- Academic advisors make efficient use of time during advising appointments
- Department emphasis on supporting students through developmental advising
- Advisors support student understanding of departmental and institutional policies and procedures

Actual Performance

The gap analysis found a number of areas in which students and staff were not performing at the desired level. To gain valuable insight into department performance, the researcher used existing data from the end of semester department surveys. The fall 2019 survey results allowed the department to gain an understanding of how students perceive interactions with academic advising staff and resources. Survey results indicated that honors students were unable to find the following information without an academic advisor:

- Honors program completion requirements
- Status on experiential learning requirements
- Answering general advising questions after hours
- Scholarship submission status

A survey of academic advisors in the honors college indicated that the following issues are prevalent:
• Inefficient use of human capital due to the repetitive nature of similar questions

• Appointments that last less than 5 minutes due to the nature of the appointment (ie: scholarship status or experiential learning requirements)

• Inability to see every student on an advisor’s caseload in a timely manner

**Gap Analysis**

Once the organizational analysis was completed, the gap analysis illuminated the areas in which the advising department needed to focus improvement. These performance gaps included the lack of a resource where students could check their honors status, course completion, experiential learning requirements, general time for program requirements, and answers to FAQs about honors or advising without directly engaging an academic advisor.

**Cause Analysis**

This research first used a comprehensive literature review to define the importance of academic advising in assisting student persistence, to validate the wide applicability of the HPT performance improvement model, and to present evidence supporting the use of a chatbot within academic advising as a useful tool to allow academic advisors to focus on more complex student needs. Based on the identified gaps in the honors college departmental advising survey, the focus of this research was on the evaluation of the AVA as an intervention tool.
**HPT Process: Interventions**

The needs-based assessment informed the design of a chatbot, which served as the intervention to address identified performance gaps. The department gap analysis provided data to justify the need to improve the existing delivery system for prescriptive academic advising information.

The intended design of the AVA chatbot was to focus on a familiar design language. It was essential to model the AVA chatbot console after text messaging or instant messenger applications. In addition to the familiarity of design language, it was also crucial for the AVA to have a responsive user interface for quick and easy deployment. The artificial intelligence and machine-learning framework used to power the AVA chatbot was part of a Google Cloud service utilized for rapid chatbot deployments. Questions can be added as training phrases into the framework, which are then translated into machine-learned data. Based on question context, the framework matches the queries to a programmed intent in order to provide personalized responses. A custom departmental database also provides information to address student queries with personalized responses. To program the database and appropriate intents, the researcher identified a list of questions frequently asked by honors college students. Questions were compiled from the department's website, emails, and conversations with academic advisors. The AVA chatbot had 545 intents programmed to respond to advising and department-related questions. Answers to these questions were added to the framework as intended responses.

The carefully considered the literature surrounding chatbot design and implementation and what constitutes successful chatbot implementation. Literature from Jain et al. (2018) and Przegalinska et al. (2019) on chatbot abilities helped shape the teams' conversation about the AVA chatbot development. Relevant contextual data from student advising conversations and
emails enriched the program intents (Almansor & Hussain, 2019; Radziwill & Benton, 2017). The AVA development focused on information retrieval, one of the three categories of chatbot approaches. Carayannopoulos (2018) stated the importance of designing for ease of information retrieval and overall convenience. The researcher and team contemplated a second category, task-oriented dialogues, but could only consistently implement one such task (Almansor & Hussain, 2019; Leuski & Traum, 2011).

The AVA chatbot application provided in-time support to students whenever they needed it, 24 hours a day, seven days a week. This type of chatbot design is an innovative approach. The researcher and team designed the AVA chatbot to work seamlessly within existing department data structures. In addition to providing personalized responses to student participants, being embedded within the department data structure allowed the AVA access to additional data.

This technology allowed for quick and effective responses that mimic human conversation through natural-language speech. This natural language, text-based, academic advising chatbot was developed by a small group of student developers working for the honors college. Student developers are part of an honors program that provides hands-on training for students interested in computer science. The application was hosted in the honors college department within the existing university web service arrangement. No identifiable student information was shared with any third-party providers. This decision was made to ensure student privacy and eliminate third-party providers' access to student information.

The design and implementation of a prescriptive academic advising chatbot allowed for more efficient use of human capital by delegating repetitious prescriptive advising to a digital medium. Student utilization of this tool lead to increased engagement with academic advising and faster, more available access to academic advising resources. In this manner, the AVA
further supported academic advisors by developing more efficient communication paths that scale with student growth unmatched by human capital (Ni et al., 2017).

**HPT Process: Evaluation of the Intervention**

The researcher evaluated the effectiveness of this prescriptive Advising Virtual Assistant (AVA) chatbot in improving the above identified performance gaps. The below items represent both formative and summative evaluation. Evaluation is a continual process in the HPT model and included the following:

- Evaluated the effectiveness of the AVA intervention
- Determined the perceived value of the AVA to participants
- Assessed the meta-evaluation data for key trends and to inform later iterations of the AVA

**Data Collection Instruments**

This section elaborated on the research questions posed in Chapter 1, which guided the data collection and the creation of data collection instruments. In this Design and Development Research (DDR) study, several data collection instruments were used to answer the four research questions.

1. **What are the demographics of students who use the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?**

   To gain an understanding of who used the AVA, data were taken directly from the application usage data. This allowed for a digital observation of the honors student population that self-selected to use the AVA for advising information. This data will be linked to the university demographic data via the student University ID number (UID).
2. **How are students using the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?**

This question was answered using data harvested from the AVA application. The application usage data captured user interactions with the chatbot. Data on user interactions with the AVA have been analyzed to understand student advising needs. Usage data within the application was queried for number of participants, question types and frequency, date and time, as well as whether the question was successfully answered (see Table 1 below.)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit of Measure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants</td>
<td>Numerical</td>
<td>Total number of active student participants (participant retention rates)</td>
</tr>
<tr>
<td>Questions types</td>
<td>Frequency, AI Response label</td>
<td>1. Average number of questions asked of the AVA in a session</td>
</tr>
<tr>
<td></td>
<td>(Word cloud data visualization)</td>
<td>2. Most frequently asked questions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Total number of topic conversations had by the AVA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. Most addressed academic advising topics</td>
</tr>
<tr>
<td>Date</td>
<td>Month, day, year</td>
<td>Most common days and times of AVA usage</td>
</tr>
<tr>
<td>Time</td>
<td>24-hour clock</td>
<td>1. Percentage of access time occurring outside of academic advising office hours</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Average time spent interacting with the AVA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Length of time using</td>
</tr>
<tr>
<td>Answers</td>
<td>Numerical</td>
<td>Questions successfully answered</td>
</tr>
</tbody>
</table>

3. **How do students perceive the Advising Virtual Assistant (AVA) chatbot as a tool for answering their academic advising questions?**

The Technology Acceptance Survey based on the Technology Acceptance Model (TAM) was used to assess students’ acceptance and usage of the AVA as an academic advising tool.
(Sánchez & Hueros, 2010). The Technology Acceptance Model (TAM) is one of the most influential and commonly used models for understanding usefulness and ease-of-use in relation to an individual’s acceptance of new technology (Isaac, Abdullah, Ramayah, & Mutahar, 2017). The TAM model gauges how users will adopt and integrate a new piece of technology in their normal life. Studies by Davis and Bagozzi emphasize that users make judgements of new technologies based on perceived ease-of-use and perceived usefulness (Mohammadi, 2015).

The construct of perceived ease-of-use is defined as the degree to which a person believes that learning how to use a particular system would be free of effort (Mohammadi, 2015). This research question was answered via a TAM survey disseminated to students who interacted with the AVA. This same question was also used to assess the perceived usefulness of the AVA application in meeting students' needs. The idea of perceived usefulness is defined as a key element of the user’s intention to acclimate to more innovative and user-friendly technologies (Mohammadi, 2015). Consequently, it was necessary to capture whether or not students perceived the AVA as a useful tool for academic advising. Hence, participants were invited to take a short, 13 question, measured survey using a 7-point Likert Scale, with options (1) strongly disagree, (2) disagree, (3) somewhat disagree, (4) neither agree or disagree, (5) somewhat agree, (6) agree, and (7) strongly agree to assess their experience with the AVA providing requested support. The TAM survey results (see Appendix 1) allowed the researcher to understand participants’ perceptions of the AVA as a tool.

4. How efficient is the Advising Virtual Assistant (AVA) chatbot at addressing prescriptive academic advising questions?
Question four provides an analysis of how the AVA meets prescriptive advising needs. The success of the application was assessed by evaluating the AVA usage data for frequency of use, types of interactions/questions, and the AVA’s response accuracy. This provided understanding about whether the AVA design strategy was successful at ensuring delivery of accurate responses to participants.

**Study Procedure**

The AVA chatbot was designed and developed to meet the needs for timely prescriptive academic advising information. The strategic placement of the AVA chatbot in the advising portal allowed easy access to valuable information regarding honors college student status as well as pertinent academic advising information. The chatbot screenshot pictured in appendix 5. The interactive design served as motivation for students to use the chatbot application. During this study, the AVA application was promoted in emails from advising staff and was also advertised in the college weekly newsletter. Student utilization of the AVA service was promoted as an extension of the academic advising office.

Participants who used the AVA were invited to complete a survey to gauge their perceptions regarding its value at the end of their login session. Honors students’ perceptions of the AVA informed ongoing changes to continually improve the chatbot throughout the study. A multi-perspective approach was used to capture both quantitative data from surveys administered through the chatbot application and participant data harvested from the AVA application. The researcher assessed the efficacy of the chatbot through usage data and the TAM survey. This approach was used to yield a greater understanding of how the AVA was utilized by participants and its effectiveness in delivering prescriptive advising support as an intervention tool.
Post-session surveys were conducted online without time and location limitations. The AVA application was first implemented within the honors advising portal in August 2020. Following the launch of the application, the researcher began reviewing survey responses after the first month in order to revise the chatbot based on the initial feedback garnered from the surveys. This strategy utilized the HPT formative evaluation process as a means to implement chatbot design improvements. This iterative process resulted in multiple updates throughout the course of the semester, including:

1. Technical updates to improve response time between Cloud services and local CRM
2. Paying for Goggle Cloud service to add more training content for accurate responses
3. Reviewing and updating training phrases

The summative evaluation process utilized survey responses combined with data captured within the application to provide quantitative data as well as themes to lend an understanding of student perceptions.

The researcher followed the data collection procedures outlined below for working with survey results from the HPT gap analysis:

1. **Strategic placement**: implementation of an academic advising portal to house the chatbot application was announced to all students actively enrolled within the honors college.
2. **Communication plan**: the creation of an advertisement through the college online newsletter and direct student email campaign.
3. **Survey plan**: All AVA participants were offered the opportunity to take a 13-item electronic survey before exiting the activity session. Participants were actively enrolled members of the honors college. If participants agreed, the survey link was shared through
the chatbot application. Upon clicking on the survey link, students were taken to a web browser to complete the Qualtrics survey. The survey results offered greater insight into student perceptions regarding AVA application usage within honors advising.

All data gathered through the Qualtrics TAM survey was downloaded data into a Microsoft Excel spreadsheet and converted into a Power BI dataset. A multi-perspective approach was used to capture quantitative data from both the AVA application and TAM surveys. The AVA usage data was also downloaded into Excel and then converted into a Power BI dataset. Table 2 includes participant usage, question frequency, time of use, and the accuracy of the AVA’s response. The goal was to identify trends and patterns in relation to user interactions with the AVA as well as the ability of the application to accurately address advising questions.

**Table 2. The Collected AVA Data Includes:**

<table>
<thead>
<tr>
<th>Units of measure</th>
<th>Variables</th>
<th>Questions when examining variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Descriptive Statistics</td>
<td>Participant usage</td>
<td>1. What is the average time spent interacting with AVA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. What is the total number of unique users</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. What is the total number of active users (by admission cohort)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. Which academic advising topics are most addressed</td>
</tr>
<tr>
<td>Descriptive Statistics</td>
<td>Question frequency</td>
<td>1. Which questions are asked most often</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Which academic advising topics are most addressed</td>
</tr>
<tr>
<td>Days of the week and 24 hour clock</td>
<td>Day/time usage</td>
<td>1. What percentage of time is the AVA accessed outside of academic advising office hours</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. What are the most common days and times of AVA usage</td>
</tr>
<tr>
<td>Descriptive Statistics</td>
<td>Accuracy of response to student inquiries</td>
<td>1. Which questions are answered successfully most often</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Which questions are more likely to result in a terminated session</td>
</tr>
</tbody>
</table>
Data Analysis

The researcher reviewed software analytics data from the AVA chatbot participant surveys. The application was constructed so that the features of the application assisted in the collection of empirical data. Students were able to use the AVA chatbot on their phones, tablets, or computers through a web browser and the TAM survey was administered to assess perceptions of the application. The researcher believed that students would feel more encouraged to share their honest perceptions of the AVA chatbot application via an online survey, thereby gathering more meaningful feedback about the application. Microsoft Excel and Power BI were used to analyze the quantitative datasets from the AVA usage data.

This study's participating department had approximately 2,457 active students, representing more than 131 different majors and 19 different colleges within a large public university located in the southeastern United States. All study participants were members of the honors college that utilized the AVA application through the honors college student portal. All active members of the honors college were invited to use the AVA application, which was open from the first week of the fall 2020 semester through the last week of classes. Due to the COVID-19 pandemic, a number of the institutions' departments were working remotely and there were challenges in getting information to students that was not COVID-19 related.

Addressing the Research Questions

RQ1: What are the demographics of students who use the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?

This question helped establish an understanding of the student demographics using the AVA chatbot. It allowed for a real understanding of what population of undergraduate students gravitate towards using the AVA as an academic advising tool. As the chatbot empowered
students to acquire information independently, capturing student demographics was necessary for improving the AVA to address student needs. It allowed for an understanding of how to best iteratively develop the AVA to meet the needs of its primary demographic audience effectively.

*RQ2: How are students using the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?*

Utilizing a quantitative approach to assess the rate of success and failure in evaluating the attributes of the AVA, a number of variables were examined to answer this research question. User interaction data, such as length of time using the chatbot, frequency of question type, chatbot performance, and chatbot rate of response were used as part of a statistical analysis. The researcher also considered the mean score and standard deviation to test the attributes of both the application and user feedback.

*RQ3: How do students perceive an Advising Virtual Assistant (AVA) chatbot as a tool for answering their academic advising questions?*

Survey data analyzed the relationship between participant perception of the AVA and its intended usefulness. Descriptive data analysis included means, frequency, percentage, and standard deviations. Based on the HPT formative and confirmative evaluation, a survey comprising demographic information and multi-item Likert scale questions was designed to evaluate user perceptions of usefulness and ease-of-use of the AVA application.

Carayannopoulous’ (2018) assertion that a chatbot can help students feel more personally connected to the instructor, and Coniam’s (2008) discussion on chatbots as conversational partners for foreign language acquisition all point to the importance of usefulness and ease-of-use.
RQ4: How efficient was the Advising Virtual Assistant (AVA) chatbot at addressing prescriptive academic advising questions?

The literature review revealed that chatbots do increase user engagement, with content being delivered by several mechanisms (Lee & Choi, 2017). Numerous articles in the literature review referenced user engagement being influenced by the user having a sense of connectivity with the chatbot or with other users (Almansor & Hussain, 2019; Przegalinska et al., 2019). Data pertaining to non-identifiable student demographic information such as gender, educational level, and major were utilized to provide context for which students interacted with the chatbot. The available literature supported the hypothesis that an AVA chatbot could successfully provide prescriptive advising information in an efficient manner. Table 3 shows which data source was analyzed to answer each of the four research questions.

Table 3. Aligned Research Questions for Data Analyses.

<table>
<thead>
<tr>
<th>Research question</th>
<th>Data sources</th>
<th>Data analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. What are the demographics of students who use the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?</td>
<td>AVA (Application) Data</td>
<td>Participant age, gender, major, year at university, and GPA. All responses will be used as part of a descriptive data analysis.</td>
</tr>
<tr>
<td>2. How are students using the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?</td>
<td>AVA (Application) Data</td>
<td>Participant interaction data, such as frequency of question type, how gender, admission cohorts, and chatbot rate of response will be used as part of a descriptive data analysis.</td>
</tr>
<tr>
<td>3. How do students perceive an Advising Virtual Assistant (AVA) chatbot as a tool for answering their academic advising questions?</td>
<td>TAM survey data</td>
<td>Used TAM data to understand the following: Perceived ease of use: 5 items, Perceived usefulness: 7 items, and Intention to use: 3 items. Content analysis: descriptive data analysis – means, frequency, and standard deviations.</td>
</tr>
<tr>
<td>4. How efficient is the Advising Virtual Assistant (AVA) chatbot at addressing prescriptive academic advising questions?</td>
<td>AVA (Application) Data</td>
<td>Application rate of successful responses. Content analysis: words phrases used by participants and AVA response intents.</td>
</tr>
</tbody>
</table>
Assumptions

Student feedback regarding general usability and effectiveness of responses was key in determining ongoing iterations of the application. The top priority of the study was to accurately determine the perceptions students had about using such an application to get answers to their prescriptive advising questions. The goal for AVA was to offer efficient and accurate delivery of academic advising information. The application also helped minimize or eliminate student wait time when attempting to access basic advising answers. For advisors, this application reduced the number of emails and office time spent addressing frequently asked questions.

Consent Process and Ethical Considerations

The researcher safeguarded participant privacy by not sharing participant information with third-party providers of any kind. Data requests were submitted to a department IT representative. The researcher received participant data that had been unidentified except for the UID. The researcher did no harm to participants and fully disclosed any COI in this process. Campus single sign-on systems were used to help secure the AVA from unscrupulous intent. Data from the AVA served as part of a comprehensive process of evaluating the effectiveness of the AVA as a tool for information delivery. Study participants were invited to participate in a digital TAM survey measuring user perception with the AVA chatbot. The study was given an Institutional Review Board (IRB) exemption status based on data collection and evaluation procedures (Appendix 6).

The design and development of the AVA was conducted by the researcher in collaboration with a six-person team of undergraduate computer science and electrical engineering majors working within an IT collaborative. The academic advisor, who is also the researcher, holds a Master’s in Education with a concentration in College Student Affairs and
more than 10 years of IT project management experience in both nonprofits and higher education. The researcher developed the original notion of the AVA as a result of his experience in IT and academic advising. All coding of the application was done by the IT student developers.

Section 3: Summary and Conclusion

Academic advisors play an increasingly important role in supporting students’ academic persistence and degree completion. A considerable amount of an academic advisor’s day is consumed responding to frequently asked questions. As evidenced in the literature review, academic advising has already seen the advent of new technology and software which enable advisors to be more efficient and better provide students with guidance and support. One of the most important aspects of academic advising is to provide mentorship to students, which was expanded through the creation of an AVA chatbot to allow advisors to spend more time on critical, student-centered tasks. This chatbot enabled students to access needed information more efficiently, and at any time they desired, thereby supporting student persistence through timely and efficient access to advising information.

Maximizing human capital by using technology to close performance gaps has the potential for a wide range of applications, particularly in higher education. The researcher anticipates that with this technology, advising resources will be more readily available to students, thus promoting academic persistence and positively impacting timely graduation. This application has the potential to extend access to information offered in a routine academic advising appointment beyond the traditional 8 a.m. to 5 p.m. office hours.

The goal of the study and application development was to demonstrate the need for innovative, in-time delivery methods of advising information and to show that a chatbot could be
a desirable and effective solution. Answers to the four research questions regarding effectiveness and user engagement informed the continuous development of the AVA chatbot. The AVA chatbot helped minimize or eliminate student wait time when attempting to access prescriptive advising information. For advisors, this application reduced the number of appointments or emails that repeated frequently asked questions. Ultimately, the use of the AVA chatbot intervention tool allowed for richer face-to-face appointments with academic advisors by giving students access to prescriptive academic advising information prior to their appointment and allowing students more time for in-depth discussions with academic advisors.
CHAPTER FOUR: RESULTS

Introduction

This study aimed to design, develop, and evaluate an automated, AI-enabled, advising system (the AVA chatbot) for delivery of academic advising and university-related information. The AVA chatbot was designed to provide timely advising and university information that surpassed traditional websites and delivered personalized advising information to students by utilizing current university records. The underlying premise was to better understand how performance support technology can assist higher education institutions by promoting efficiency of advising services while improving student performance.

Chapters 1 and 2 highlighted the need for timely access to advising and university information to better support student academic success. Chapter 3 explained how the current study employed the Design and Development Research (DDR) principles to guide the evaluation process of the AVA chatbot as a performance technology tool to support individual students’ advising needs (Richey & Klein, 2007) which were more challenging to meet during the COVID-19 pandemic.

This chapter presents the findings of the AVA chatbot evaluation regarding the conditions which support the utilization of an AVA chatbot application and what facilitates chatbot use by participants. The following approach towards data collection procedures was implemented. First, dialogues between users and the AVA were reviewed and analyzed. Then, data were collected from the AVA chatbot to determine who used the AVA and how they
engaged in conversation with it. Finally, participants' perceptions towards the AVA were collected from the Technology Acceptance Model (TAM) survey, which is recognized as a robust and powerful tool for predicting the acceptance of information technology products (Hsiao & Yang, 2011). This evaluation study was developed within an honors college due to the large variety of students, majors, and academic credentials in said college. This honors college, housed at a large public institution of higher education, is located in the southeastern United States. The design and development process contributed to the empirical knowledge base for developing the AVA. The AVA datasets were provided with the college dean's approval and requested from the department's IT staff. The data gathered as part of the study were requested at the end of the semester and were received in a Microsoft Excel Comma-Separated Values document devoid of personally identifiable information except University ID numbers.

**RQ1: What are the demographics of students who use the Advising Virtual Assistant (AVA) chatbot to answer their academic advising questions?**

**Table 4. Study Participant Demographics.**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Items</th>
<th>Entries</th>
<th>Percentages (%)</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Female</td>
<td>66.8</td>
<td>151</td>
<td>151</td>
</tr>
<tr>
<td></td>
<td>Male</td>
<td>33.2</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>16-18</td>
<td>164</td>
<td>17</td>
<td></td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>300</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>221</td>
<td>23</td>
<td></td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>160</td>
<td>17</td>
<td></td>
</tr>
<tr>
<td></td>
<td>22-24</td>
<td>90</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Admit Year</td>
<td>F16</td>
<td>29</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F17</td>
<td>104</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F18</td>
<td>185</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SU19</td>
<td>5</td>
<td>.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F19</td>
<td>349</td>
<td>37.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SU20</td>
<td>12</td>
<td>1.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>S20</td>
<td>8</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>F20</td>
<td>245</td>
<td>26</td>
<td></td>
</tr>
<tr>
<td>International Students</td>
<td>Yes</td>
<td>11.5</td>
<td>26</td>
<td></td>
</tr>
<tr>
<td>Domestic Students</td>
<td>Yes</td>
<td>88.5</td>
<td>200</td>
<td></td>
</tr>
</tbody>
</table>
This section presents the research findings from the fall 2020 semester of the AVA chatbot use within the honors college. A total of 226 students completed advising sessions using the AVA chatbot application within the honors portal. Participant demographics broken down by gender consisted of 151 females (67%) and 75 males (33%), with a male age mean of 19.76 (SD=1.54) and female age mean of 19.71 (SD=1.26). Table 4 further shows participant engagement by admission cohorts. Separating cohorts by admission year showed how each cohort interacted with the AVA chatbot via the number of participant text entries. Gender demographics were representative of the target population in the honors college, which has approximately 1,476 females (60%), 950 males (39%), and 31 who listed gender as unavailable for a total of 2,457 students. A total of 939 conversation entries were made during one semester, including 678 different questions spanning 12 comprehensive advising topics.

![Participant Usage by Occurred Month and Gender](image)

**Figure 2.** Total AVA interactions by month and gender

Among the 226 participants, 38 students (17%) engaged with AVA multiple times over the course of the study. Figure 2 illustrates the number of total interactions with AVA broken out by gender over the five months. Interactions with AVA consist of any information the participant inputs into AVA to either ask a question or respond to a question. Between August 2020 and
December 2020, the most repeated usage occurred during the month of November 2020. The number of users who accessed AVA repeatedly was also high in October. When considering gender, both male and female students used the AVA repeatedly the most between the months of October and November. Two female participants out of the total demonstrated AVA use monthly, but there was no similar male counterpart.

Students from a total of 10 different academic colleges with 55 programs were represented within this study, with the majority of participants from STEM programs. The majority of participants in the study were identified as the Fall 2019 cohort. The researcher categorized participants based on entry year instead of credit hours because students entering as freshmen into this honors college often bring with them accelerated credit hours from Advanced Placement (AP), International Baccalaureate (IB), or dual enrollment from their local college or university. These credit hours typically elevate their status from a first-year student to sophomore or junior status. For clarity, participant categorization was based on year of entry instead of credit hours.

**RQ2: How are students using the AVA chatbot to answer academic advising questions?**

To answer the above research question, the AVA application log data were analyzed to understand how participants interacted with the AVA in terms of the application usage listed below:

1. Frequency of question type:
   a. Most requested question categories
   b. Frequency of intent responses
   c. Number of participant-specific questions
2. Participant usage (user interaction data)
a. Length of time using the chatbot

b. Day and time of usage

c. How admission cohorts interacted with AVA

3. Chatbot performance

a. Accuracy of response to student inquiries

b. Chatbot rate of response

The 226 study participants produced a significant amount of data while engaging with the AVA. Careful consideration was used when analyzing the frequency of question occurrence and the generated AVA response intents. See appendix 7 for samples of participant inputs. With the goal of AVA chatbot deployment centering around providing timely delivery of prescriptive advising information, it was important to understand the types of questions being asked and the frequency patterns. As shown in Table 5, the question intent category lists the questions with the highest number of generated intent occurrences.

**Table 5. Categories of Questions Most Addressed by AVA.**

<table>
<thead>
<tr>
<th>Question Intent Category</th>
<th>Example Questions</th>
<th>Number of Questions</th>
<th>Intent Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Advisor Related - Questions asked about Academic Advisors</td>
<td>“Who is my advisor?” “Who is my honors advisor?”</td>
<td>4</td>
<td>84</td>
</tr>
<tr>
<td>2. Global Experience - Questions related to the honors requirement for global experience and form submission</td>
<td>“Tell me about global experiences?” “Can I take Spanish to cover one of my global experiences?”</td>
<td>53</td>
<td>65</td>
</tr>
<tr>
<td>3. Honors Courses Requirements - general information about honors courses</td>
<td>“What are the honors core courses?”</td>
<td>14</td>
<td>15</td>
</tr>
<tr>
<td>4. Advising Appointment Related -</td>
<td>“Are there walk in appointments?”</td>
<td>43</td>
<td>45</td>
</tr>
</tbody>
</table>
Table 5. (Continued)

<table>
<thead>
<tr>
<th>Questions related to making or scheduling an appointment with an academic advisor</th>
<th>“Can I schedule a walk in appointment?”</th>
</tr>
</thead>
<tbody>
<tr>
<td>5. Community Service - Questions about community service requirement and form submission</td>
<td>“where I can find community service opportunities?”</td>
</tr>
<tr>
<td>6. Honors Research Track - information about the track and how to complete the track</td>
<td>“What are the Honors Research Tracks?”</td>
</tr>
<tr>
<td>7. Honors Scholarships - general information about honors scholarship and submission</td>
<td>“where can i apply for scholarships?”</td>
</tr>
</tbody>
</table>

Table 5 displayed question categories most addressed by the AVA based on AVA chatbot response intents. The intent labels are programed keywords from the AVA's knowledge database. The majority of the participants asked questions connected with one of the seven question categories listed in Table 5. These AVA intent labels were created as part of the AVA chatbot framework. Intents categorize responses within the chatbot framework to quickly answer participant questions (Maroengsit, Piyakulpinyo, Phonyiam, Pongnumkul, Chaovalit, & Theeramunkong, 2019). In this study, the AVA chatbot had a total of 545 intents programmed to respond to advising and department-related questions.

The AVA chatbot intents were programmed to highlight common university resources often used by students in the honors college. The AVA chatbot responses were designed to be centered around delivery of prescriptive academic advising, which led to convenient category classifications of question types and AVA responses. The miscellaneous category of questions typically involved questions that were more complex or non-prescriptive in nature. An example
of a non-prescriptive question was, "What's the best path for me to take?" Such non-prescriptive questions are difficult for the AVA chatbot to answer because the question requires an understanding of the student’s needs and academic experience. For these questions, students need a human advisor to guide them in conversation about academic and professional goals. The lack of clarity as to what was meant by the word "path" also made it difficult for the AVA to provide the participant with answers that met their advising needs.

<table>
<thead>
<tr>
<th>Participant:</th>
<th>I am looking for global experience activities</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVA:</td>
<td>Do you want to know options that fulfill one completed global experience activity or two completed global experience activities?</td>
</tr>
<tr>
<td>Participant:</td>
<td>one</td>
</tr>
<tr>
<td>AVA:</td>
<td>To complete one global activity, students can: Complete levels 1 and 2 of a foreign language through coursework or demonstrated proficiency. Complete any Honors or Education Abroad international trip. Would you like to know more options?</td>
</tr>
<tr>
<td>Participant:</td>
<td>no</td>
</tr>
<tr>
<td>AVA:</td>
<td>No problem! What else can I help you with?</td>
</tr>
</tbody>
</table>

Figure 3. A participant’s discussion about global experience

Within each question category, there were several sub-questions asked. Participants asked 53 different global experience-related questions triggering this intent. The keyword connecting the intents was “global experience” with 65 intent occurrences. The number of occurrences captures data from both question and keyword recurrence. For the community service category, 14 questions were identified, such as, “Should I put my service at the top of my transcript for convenience?” and, “What are some ideas for community service?” The word “service” connected AVA intents found in this category, and the AVA chatbot answered the questions to the best of its ability based on the context of the participant question or keyword phrases. Below is a sampling of questions regarding global experience which shows the variety of questions
from a single category. This variety made it difficult for the AVA to consistently give accurate responses:

- “Can I take Spanish to cover one of my global experiences”
- “Is there a way to see what fulfills global experience?”
- “When I try to submit my global experience prove, i can't click ‘submit’”

**Participant Usage (User Interaction Data)**

It was not possible to evaluate any of the participant usage data automatically. Beginning with the amount of time participants spent engaging with the AVA chatbot, the data varied between cohorts and between international and domestic students. A thorough, manual analysis of the chatbot dataset was needed to calculate the length of time, days of use, and admission cohort interactions.

Generally, participants spent approximately 2.5 minutes using the AVA chatbot. The Fall 2019 and Fall 2020 were the largest two cohorts in the study. Fall 2019 cohort members were the largest cohort in the study and the most active. Students in this cohort spent an average of 3.4 minutes using the AVA application. The cohort found to engage the least amount of time with the application was the Fall 2017 cohort, with an average usage time of 1.71 minutes. International students across all program entrance years spent an average of 4.15 minutes engaged with the AVA chatbot.

The majority of chatbot interactions took place during regular business hours of 8 to 5, with the bulk occurring in the afternoon. Mondays and Fridays were the top two days for participant usage, with a total of 303 AVA interactions on Mondays and 207 interactions on Fridays. The number of participant interactions on the weekends increased during peak advising times, notably in November before course registration for the upcoming semester began.
November was also the month with the most consistent use, with a total of 441 AVA interactions which were spread fairly evenly throughout the month. A closer look at the data revealed that several of these participants were repeat users.

The majority of conversations across all cohorts, regardless of gender, were about academic advising topics. A look at both female and male cohorts to better understand commonalities and differences was important. To accomplish this task, both male and female responses by cohort were reviewed for patterns and themes. Since the advising question category ranked first for both genders, it was ideal for a more in-depth comparison.

Beginning with the two largest cohort groups, the Fall 2019 and Fall 2020 cohorts were most likely to make inquiries about advisors and scheduling-related questions (see Table 5, Question Intent Categories 1 and 4). The Fall 2018 cohort ranked third in asking these categories of questions. The engagement within this question category showed the different ways various cohorts conversed with the AVA chatbot when requesting and receiving advising information. Further dissection of the remaining cohorts found some differences but more commonalities between the Fall 2017, Summer 2019, and Summer 2020 cohorts as the study cohort populations least likely to pose academic advising and scheduling-related questions.

**Chatbot Performance**

Evaluating the AVA chatbot accuracy required a look at the AVA data and participants' words. AVA chatbot response rate was essential to the chatbot's goal of delivering advising information. There were a total of 617 successfully generated response intents, representing 65.7% accuracy. Of the 226 participants who used the AVA, only 185 used complete, structured sentences when engaging with the AVA, meaning the input contained one main clause and a complete idea. Of the 226 total participants, 103 participants chose to engage with the AVA
chatbot by using keyword searches. Out of the 201 keyword searches used while interacting with the AVA, 96% were prescriptive. For these keyword searches, 70 participants were female and 30 were male.

During the first half of the semester, the AVA correctly answered participants' questions 62% of the time. Within the same timeframe, 38% of questions were answered incorrectly. Requested information not included in the AVA's knowledge database was updated once a month with new intents. In the last half of the semester, the AVA's response rate increased to 67% accuracy when responding to participant requests. The number of incorrect responses decreased to 33%.

**AVA Dialogue Flow**

Engagement with the AVA varied based on the participant's phrasing of words and conversation goals. Looking at conversation flow helps to understand how participant satisfaction and chatbot ability both impact participant interaction with the AVA. The degree of accuracy in a given response generally corresponds to the degree of the participant’s satisfaction with the AVA.

![Diagram](image)

**Figure 4.** Chart showing participant retention based on conversation flow
The flow of conversations served as a gauge of participant experience by demonstrating how students used the AVA chatbot. Figure 4 above shows participant retention for four users based on conversation flow with the AVA chatbot. All AVA conversations began at the same point, and the figure above shows how the conversation flowed within the AVA chatbot. The conversations shown in Figure 4 are actual conversations had by participants. The black lines represent conversations that continued while the participants explored what the application could answer, and the red hexagon indicates where participants ended their session with the AVA. The green arrow in the diagram above represents one conversation that extended beyond the diagram image. The green circles indicated where participants received a correct response from the AVA based on their question or keyword search, and the red circles indicated where they received an incorrect answer. Figure 4 demonstrates that participants who received more accurate responses continued to ask questions more often than those who received incorrect responses.

**RQ3: How do students perceive an Advising Virtual Assistant (AVA) chatbot as a tool for answering their academic advising questions?**

The desire to understand how AVA performed as an intervention for timely information delivery came from the identifiable needs discussed as part of the HPT assessment conducted by the participating college. AVA application data is only part of the performance measure for success. The other part is the TAM Survey results. The TAM model states that users decide to use a technology based on two main components: perceived ease of use and perceived usefulness. The researcher hypothesized that participants within this age group would naturally gravitate to the AVA application because of convenience and accessibility. It was hypothesized that participants would report positive perceptions while engaging with the AVA based on the demographics of this participant group and specifically their familiarity with texting applications, virtual assistant speakers, smart devices, and similar technologies connected with social media.
The TAM survey was used to evaluate participants’ experiences with the AVA in terms of the application’s perceived usefulness and ease-of-use. All participants who used the application were offered the opportunity to voluntarily take the TAM survey. This survey link was automatically offered through the honors portal application. Out of the 226 participants who utilized the AVA application, 73 attempted to complete the TAM survey. Only 65 participants submitted a complete TAM survey as shown in Table 6. A total of 56 unique participants completed the survey, providing an acceptable response rate of 24.7%. Of the 39 participants who used the AVA for more than one activity session, 14 participated in the TAM survey. A total of 49 females (75%), 15 males (23%), and one participant who was not identifiable participated in completing the TAM survey. One survey respondent was removed from the dataset due to an unidentifiable student number.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Items</th>
<th>Number</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Female</td>
<td>49</td>
<td>5.86</td>
<td>.98</td>
</tr>
<tr>
<td></td>
<td>Male</td>
<td>15</td>
<td>5.61</td>
<td>1.52</td>
</tr>
<tr>
<td>Admit Cohort</td>
<td>F17</td>
<td>6</td>
<td>5.92</td>
<td>.52</td>
</tr>
<tr>
<td></td>
<td>F18</td>
<td>9</td>
<td>6.10</td>
<td>.37</td>
</tr>
<tr>
<td></td>
<td>F19</td>
<td>28</td>
<td>5.76</td>
<td>.44</td>
</tr>
<tr>
<td></td>
<td>F20</td>
<td>20</td>
<td>4.65</td>
<td>2.56</td>
</tr>
<tr>
<td>International Students</td>
<td>Yes</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Domestic Students</td>
<td>Yes</td>
<td>58</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 6. TAM Demographic Information.

### Table 7. Means and Standard Deviations of TAM Items.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived ease of use</td>
<td>Overall</td>
<td>6.16</td>
<td>1.15</td>
</tr>
<tr>
<td></td>
<td>AVA chatbot is easy to use</td>
<td>6.16</td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td>Learning to use the AVA chatbot is easy for me</td>
<td>6.34</td>
<td>1.02</td>
</tr>
<tr>
<td></td>
<td>AVA chatbot is easy to understand</td>
<td>6.19</td>
<td>1.03</td>
</tr>
<tr>
<td></td>
<td>AVA chatbot is convenient</td>
<td>5.94</td>
<td>1.37</td>
</tr>
<tr>
<td>Perceived usefulness</td>
<td>Overall</td>
<td>5.67</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>AVA chatbot helps to save time</td>
<td>5.89</td>
<td>1.44</td>
</tr>
<tr>
<td></td>
<td>AVA chatbot requires minimal effort</td>
<td>5.97</td>
<td>1.18</td>
</tr>
</tbody>
</table>
The data from the TAM survey questions are displayed in Table 7. Table 8 shows perceived ease-of-use, which used the four questions discussed in Chapter Three to identify how participants perceive the AVA as an advising tool. Based on the overall average score for perceived ease-of-use, participants found AVA easy to use. Both the overall score for perceived usefulness and for intention to use, shown in Table 7, indicate that participants somewhat agreed with both constructs.

**Table 7. Means and Standard Deviations of Perceived Ease-of-Use (by gender).**

<table>
<thead>
<tr>
<th>Questions</th>
<th>Female n= 49</th>
<th>Male n=15</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVA chatbot helps me to be self-reliant</td>
<td>5.73</td>
<td>1.36</td>
</tr>
<tr>
<td>AVA chatbot helps to improve my knowledge</td>
<td>5.60</td>
<td>1.48</td>
</tr>
<tr>
<td>AVA chatbot helps to improve my performance</td>
<td>5.11</td>
<td>1.60</td>
</tr>
<tr>
<td>AVA chatbot is effective</td>
<td>5.68</td>
<td>1.34</td>
</tr>
<tr>
<td>AVA chatbot is efficient</td>
<td>5.68</td>
<td>1.47</td>
</tr>
<tr>
<td>Intention to use</td>
<td>Overall</td>
<td></td>
</tr>
<tr>
<td>I plan to use the AVA chatbot for my advising questions</td>
<td>5.14</td>
<td>1.66</td>
</tr>
<tr>
<td>I am more likely to use the AVA chatbot over a search engine to find answers about academic requirements in the future</td>
<td>5.28</td>
<td>1.70</td>
</tr>
</tbody>
</table>

*Note: minimum score: 1 (strongly disagree); Maximum score: 7 (Strongly agree)*

The data from the TAM survey questions are displayed in Table 7. Table 8 shows perceived ease-of-use, which used the four questions discussed in Chapter Three to identify how participants perceive the AVA as an advising tool. Based on the overall average score for perceived ease-of-use, participants found AVA easy to use. Both the overall score for perceived usefulness and for intention to use, shown in Table 7, indicate that participants somewhat agreed with both constructs.

**Table 8. Means and Standard Deviations of Perceived Ease-of-Use (by gender).**

<table>
<thead>
<tr>
<th>Questions</th>
<th>M (SD)</th>
<th>Female n= 49</th>
<th>Male n=15</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. AVA chatbot is easy to use</td>
<td>6.16 (.18)</td>
<td>6.38 (.94)</td>
<td>5.44 (1.54)</td>
</tr>
<tr>
<td>2. Learning to use the AVA chatbot is easy for me</td>
<td>6.34 (.102)</td>
<td>6.47 (.77)</td>
<td>5.75 (1.64)</td>
</tr>
<tr>
<td>3. AVA chatbot is easy to understand</td>
<td>6.19 (.103)</td>
<td>6.32 (.72)</td>
<td>5.75 (1.56)</td>
</tr>
<tr>
<td>4. AVA chatbot is convenient</td>
<td>5.94 (.137)</td>
<td>6.06 (.121)</td>
<td>5.38 (1.73)</td>
</tr>
</tbody>
</table>

Participants were broken down into gender categories in Table 8 and the results revealed that male students found the AVA slightly less useful than female students. When looking at survey question number 2 (“Learning to use the AVA chatbot is easy for me”), participants found the AVA easy to learn how to use. However, male participants again rated the AVA as less easy to learn than female participants.
Table 9. Means and Standard Deviations of Perceived Ease-of-Use (by cohorts).

<table>
<thead>
<tr>
<th>Item</th>
<th>F17</th>
<th>F18</th>
<th>F19</th>
<th>F20</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVA chatbot is easy to use</td>
<td>6.00</td>
<td>6.56</td>
<td>6.27</td>
<td>5.85</td>
</tr>
<tr>
<td></td>
<td>(1.41)</td>
<td>(.68)</td>
<td>(1.06)</td>
<td>(1.39)</td>
</tr>
<tr>
<td>Learning to use the AVA chatbot is easy for me</td>
<td>6.67</td>
<td>6.44</td>
<td>6.42</td>
<td>6.10</td>
</tr>
<tr>
<td></td>
<td>(.47)</td>
<td>(.68)</td>
<td>(.88 )</td>
<td>(1.37)</td>
</tr>
<tr>
<td>AVA chatbot is easy to understand</td>
<td>6.50</td>
<td>6.56</td>
<td>6.27</td>
<td>5.80</td>
</tr>
<tr>
<td></td>
<td>(.50)</td>
<td>(.50)</td>
<td>(.90)</td>
<td>(1.36)</td>
</tr>
<tr>
<td>AVA chatbot is convenient</td>
<td>6.50</td>
<td>6.22</td>
<td>5.81</td>
<td>5.90</td>
</tr>
<tr>
<td></td>
<td>(.50)</td>
<td>(1.03)</td>
<td>(1.59)</td>
<td>(1.37)</td>
</tr>
</tbody>
</table>

Table 9 separates participants by their respective admission cohort. Our two largest populations within the study were the Fall 2019 and Fall 2020 cohorts (based on semester of admission to the honors college). These two cohorts represented a large number of the AVA participants, as well as survey participants. When organized by the entry term, the Fall 2018 cohort rated the AVA as easier to use than did the Fall 2019 and Fall 2020 cohorts. The all 2017 cohort rated AVA higher for survey question 2, regarding ease of learning to use AVA than any other group. On average, the newer cohorts rated ease-of-use and easy to learn at a lower rate.

Table 10. Means and Standard Deviations of Perceived Usefulness.

<table>
<thead>
<tr>
<th>Questions</th>
<th>Female</th>
<th>Male</th>
<th>F’17</th>
<th>F’18</th>
<th>F’19</th>
<th>F’20</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. AVA chatbot helps to save time</td>
<td>5.89</td>
<td>5.98</td>
<td>5.60</td>
<td>6.33</td>
<td>6.56</td>
<td>5.81</td>
</tr>
<tr>
<td></td>
<td>(1.44)</td>
<td>(1.36)</td>
<td>(1.62)</td>
<td>(0.75)</td>
<td>(0.50)</td>
<td>(1.69)</td>
</tr>
<tr>
<td>2. AVA chatbot requires minimal effort</td>
<td>5.97</td>
<td>6.13</td>
<td>5.47</td>
<td>5.83</td>
<td>6.11</td>
<td>6.19</td>
</tr>
<tr>
<td></td>
<td>(1.18)</td>
<td>(1.01)</td>
<td>(1.50)</td>
<td>(0.69)</td>
<td>(1.29)</td>
<td>(1.04)</td>
</tr>
<tr>
<td>3. AVA chatbot helps me to be self-reliant</td>
<td>5.73</td>
<td>5.81</td>
<td>5.47</td>
<td>6.17</td>
<td>6.22</td>
<td>5.73</td>
</tr>
<tr>
<td></td>
<td>(1.36)</td>
<td>(1.29)</td>
<td>(1.54)</td>
<td>(0.90)</td>
<td>(0.92)</td>
<td>(1.40)</td>
</tr>
<tr>
<td>4. AVA chatbot helps to improve my knowledge</td>
<td>5.60</td>
<td>5.77</td>
<td>5.07</td>
<td>5.83</td>
<td>6.00</td>
<td>5.50</td>
</tr>
<tr>
<td></td>
<td>(1.48)</td>
<td>(1.34)</td>
<td>(1.73)</td>
<td>(0.37)</td>
<td>(1.33)</td>
<td>(1.69)</td>
</tr>
<tr>
<td>5. AVA chatbot helps to improve my performance</td>
<td>5.11</td>
<td>5.17</td>
<td>4.93</td>
<td>5.00</td>
<td>5.44</td>
<td>5.08</td>
</tr>
<tr>
<td></td>
<td>(1.60)</td>
<td>(1.56)</td>
<td>(1.73)</td>
<td>(1.29)</td>
<td>(2.01)</td>
<td>(1.64)</td>
</tr>
<tr>
<td>6. AVA chatbot is effective</td>
<td>5.68</td>
<td>5.77</td>
<td>5.40</td>
<td>5.83</td>
<td>6.00</td>
<td>5.54</td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(1.26)</td>
<td>(1.54)</td>
<td>(0.69)</td>
<td>(1.25)</td>
<td>(1.50)</td>
</tr>
<tr>
<td>7. AVA chatbot is efficient</td>
<td>5.68</td>
<td>5.73</td>
<td>5.53</td>
<td>5.83</td>
<td>5.67</td>
<td>5.73</td>
</tr>
<tr>
<td></td>
<td>(1.47)</td>
<td>(1.41)</td>
<td>(1.63)</td>
<td>(0.69)</td>
<td>(1.70)</td>
<td>(1.56)</td>
</tr>
</tbody>
</table>
Table 10 contains data for perceived usefulness. Participants rated the AVA application at a lower rate in comparison to ease of use. Females rated the application as being more useful than male participants. The fall 2020 cohort rated questions about perceived usefulness the lowest out of the four participating cohorts. Question number 5 (“AVA chatbot helps to improve my performance”) was rated the lowest across all genders and cohorts.

Both males and females found the AVA chatbot as most useful in Questions 1, 2, and 3 (saves time, requires minimal effort and helps me to be self-reliant). Question 2 (“AVA chatbot requires minimal effort”) was rated the highest across all genders and cohorts. Question 1 (“AVA chatbot helps to save time”) was the next highest rated question overall. Questions regarding economy of time (“helps save time”) and convenience of use (“requires minimal effort”) were useful to determine the role of the AVA as an intervention tool to address student performance gaps. The results provided support for the use of the AVA chatbot as an intervention tool.

**Table 11.** Means and Standard Deviations of Intention to Use.

<table>
<thead>
<tr>
<th>Questions</th>
<th>Female n=49</th>
<th>Male n=15</th>
<th>F’17</th>
<th>F’18</th>
<th>F’19</th>
<th>F’20</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I plan to use the AVA chatbot for my advising questions</td>
<td>5.14 (1.66)</td>
<td>4.75 (1.71)</td>
<td>5.12 (1.83)</td>
<td>5.89 (1.37)</td>
<td>5.12 (1.83)</td>
<td>5.00 (1.67)</td>
</tr>
<tr>
<td>2. I am more likely to use the AVA chatbot over a search engine to find answers about academic requirements in the future.</td>
<td>5.28 (1.70)</td>
<td>4.81 (1.94)</td>
<td>5.38 (1.90)</td>
<td>5.67 (1.70)</td>
<td>5.38 (1.90)</td>
<td>5.25 (1.55)</td>
</tr>
</tbody>
</table>

Table 11 includes data regarding intention to use. The questions in this category directly measured whether or not participants’ behaviors would indicate AVA use in the future. Similar
to previous sections, females rated intention to use the AVA higher than male students. The Fall 2020 cohort participants rated intention to use the AVA lower than other cohorts. Participants from the Fall 2017 and Fall 2019 cohorts rated both questions in this category identically. Question number 2 (“I am more likely to use the AVA chatbot over a search engine to find answers about academic requirements in the future”) was the highest rated question in the intention to use category by both male and female participants. The results indicate positive AVA chatbot use intentions by study participants.

**TAM Survey Data Conclusion**

The TAM survey data suggests that study participants overall agreed with the survey questions, rating the AVA chatbot positively. The TAM survey used a 7-point Likert scale. Within all three categories, male students consistently rated the AVA less favorably than female students. Range for mean scores by male participants was as low as 4.75 up to 5.75 as the highest score. The same range for female students was as low as 5.17 up to 6.47 as the high score. However, that difference in scoring does not hold true when looking at all other responses. Besides the gender differences between males and females, grouping participants as cohorts by year showed a variation in results. For example, Fall 2020 cohort participants consistently rated the AVA lower than all other cohorts. The Fall 2018 cohort consistently rated the AVA with higher scores than did other cohorts. This data supports the idea that both gender and term of entry (cohort) played a role in influencing participant perception of the AVA chatbot.
RQ4: How efficient is the Advising Virtual Assistant (AVA) chatbot at addressing prescriptive academic advising questions?

Transitioning from the TAM survey results, a content analysis of the collected AVA application data was performed. As part of a formative evaluation, the input and output of the AVA application was evaluated. Both the AVA application and participant usage data were analyzed for the communicated content (how the AVA responded to participants and how participants responded to the AVA). This process provided a means to assess whether or not the content captured by the AVA supported the stated research hypothesis. Participant questions were placed into three distinct categories based on question type:

1. Whether or not a participant input was considered an actual question. For example, inputs such as “no” would not be listed under the question category.
2. Whether or not the input information was in response to AVA's follow-up questions to participants.
3. Whether participants chose to use keywords to search the AVA.

After analyzing the input of each category, questions were then further separated into prescriptive or non-prescriptive in nature. An example of a prescriptive question is, "who is my advisor?" An example of a non-prescriptive question is “what’s my best career path?” This distinction was important because AVA responses were designed to specifically address prescriptive advising questions. Non-prescriptive advising questions are beyond the scope of the AVA chatbot and should instead be answered during live advising sessions.

As part of this evaluation process, the decision was made not to use the AVA application framework's built-in scoring system because a more accurate evaluation was achieved by manually sorting the data. Manual calculations of the response rates were obtained by first categorizing inputs into three categories: Nonquestion (N), Question (Q), and Keywords (K)
This process allowed effective comparison of participant inputs to appropriate responses. Several unidentified words were marked as N because the researcher could not identify what the participant was trying to say. For example, words like “Ping” or statements like “the problem is that I can’t” or “no bye” belong to this category.

**Table 12.** Items that Triggered Incorrect AVA Intents.

<table>
<thead>
<tr>
<th>Gender</th>
<th>Item</th>
<th>Nonquestions (N)</th>
<th>Question (Q)</th>
<th>Keyword(K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>Incorrect</td>
<td>27</td>
<td>68</td>
<td>17</td>
</tr>
<tr>
<td>Female</td>
<td>Incorrect</td>
<td>37</td>
<td>120</td>
<td>53</td>
</tr>
</tbody>
</table>

**Participant:** Who is my advisor?

**AVA:** I looked it up for you and it looks like your Honors College advisor is Mr. Brown. Do you want to schedule an appointment?

**Participant:** Yes

**AVA:** Great. [Click here](#) to schedule an appointment through our online system. When asked if you know who you would like to meet with, select “Yes,” enter your advisor’s name, and you are good to go.

**Participant:** Thanks!

**AVA:** No problem! Let me know if you have any other questions or concerns that I can help you with. 😊

**Participant:** What are the honors academic requirements?

**AVA:** Are you a first time in college student or a transfer/continuing student?

**Participant:** transfer

**AVA:** To graduate with honors as a transfer/continuing student, you must complete the following:
- 4 Honors Core (IDH) Courses, including Research or Discovery track
- 25 hours of community service
- 2 Global Experiences 😊

Ask me about global experiences to learn more about ways students can complete it.

**Figure 5.** A participant’s academic advisor-related inquiry

Overall, the AVA application finished the study with an average accuracy rate of 65.7% and 59.2% for keyword searches specifically. There were 477 written questions asked of the
AVA by the 226 participants during the semester. The AVA-generated conversations produced 261 intent responses for participants. The AVA generated conversation to help clarify participant requests for more precise personalized responses. Of the 322 incorrect intent responses, 112 (34.8%) were directed to male participants and 210 (65.2%) were directed to female participants. The incorrect intent responses were generated from 188 questions, 70 keywords, and 64 non-question text entries input by participants engaged with the AVA.

The total number of interactions by users was 939. The total number of queries based on keyword searches was 201, and the total number of questions asked was 477. The number of items identified as participant responses to AVA-generated follow-up questions was 261. Questions that are labeled as prescriptive questions always generate the same response regardless of who asks the question. For example, "how do I see honors requirements?" would prompt the same response from the AVA each time. Even in the case of a question such as "who is my advisor?" the response was only personalized to a degree, namely, based on the student’s current major. Some students chose to meet with other advisors, but this information is not available to the AVA. Of the 477 questions, 85.6% were found to be prescriptive as shown in Figure 5.

Conclusion

All four research questions were analyzed and yielded useful data supporting the hypothesis that the AVA chatbot would be a useful intervention tool for students. This study took place during the fall 2020 semester and was impacted by the COVID-19 pandemic. These conditions presented unique circumstances which were challenging in regard to encouraging participant use and engagement with the AVA chatbot. Still, this extraction of AVA metadata combined with the TAM survey data results provided a rich dataset that yielded valuable insight into who used the chatbot and how participants engaged with it. Data indicated that the AVA
chatbot was perceived as having acceptable response accuracy by participants. Positive perceptions of the AVA chatbot were evidenced by the data on perceived ease-of-use, perceived usefulness, and intention to use. Of these three survey categories, the AVA scored lowest on intention to use and highest on perceived ease-of-use. Finally, the researcher conducted a comprehensive evaluation to assess the appropriateness of the AVA’s responses to participant questions. Further elaboration of the findings and results of this study can be found in Chapter 5.
CHAPTER FIVE:
DISCUSSION AND CONCLUSION

Introduction

The purpose of this study was to design an automated intervention to address student performance by providing timely access to prescriptive advising information. Allen & Smith (2006) defined prescriptive advising as an authoritative approach to delivering information from advisors to students and was therefore well suited for delivery via the AVA chatbot. This study focused on examining the behaviors of participants who used the AVA application to obtain advising-related information. The performance gap being addressed by the AVA chatbot was the lack of timely access to advising-related information. The AVA, an AI-enabled chatbot, was developed as a text-based conversational agent focusing on prescriptive advising with information curated by academic advising professionals. The AVA was positioned to serve as an efficient way for study participants to gain academic advising knowledge and to encourage progress towards degree completion.

This chapter begins with an overview of the study results and and expands on these results via discussion in relation to academic advising and chatbot application literature. The limitations and implications of the AVA chatbot on higher education practice will be included in the discussion of results. This chapter will conclude with recommendations for further research.
Discussion of the Findings

The AVA chatbot effectively delivered advising-related information to study participants, acting as a beta-test for incorporating an AI-enabled chatbot into a student information portal. The research questions for this study were also successfully addressed. Research question 1 was successfully answered by analyzing the participants' interaction based on gender, admission cohort, major, and the number of questions posed to the AVA. Chatbot performance is often evaluated by analyzing user experience satisfaction (Maroengsit et al., 2019). In this study, both the AVA chatbot data and user satisfaction experiences are evaluated using TAM Survey's perceived ease-of-use, perceived usefulness, and intention to use.

Two sets of demographic data were discarded after data collection: participant GPA and participant age. The study found no significant relationship between GPA and AVA chatbot usage. The results indicated that study participants had an average GPA of 3.80 (.22) compared to the overall honors college GPA of 3.75. The participant age data did not represent meaningful findings. Looking at admission cohorts did yield greater value as they represented a level of experience that could be further analyzed. The older cohorts versus the newer cohorts was a comparison of interest because there were differences between participant usage. Based on the analytical data from the AVA chatbot, cohort admission term did play a role in participant interaction with the AVA. The majority of students who participated in the study had entered into the university as first time in college students. The second largest demographic population in the study were continuing and transfer students. The AVA’s efficiency was critical for positive participant perception. The fall 2020 was the only cohort required to see an academic advisor, which contributed towards the study participants’ engagement peak during the middle-to-end of the term. At this time, the demands on the academic advising staff was also at its highest as
students were planning for the next semester. The AVA results were encouraging because the response rates towards the end of the semester were higher than at the start of the semester, demonstrating that the AVA chatbot functions as an additional useful advising resource for students.

As stated by Carayannopoulos (2017), chatbots are communication tools. Participants’ behaviors showed how communicating with the AVA yielded timely advising information. Nwankwo (2017) found that chatbots require strong data structures to return a personalized user experience comparable to human interactions. The initial design of the AVA's knowledge base supported the chatbot’s ability to personalize responses to individual participants. The AVA was also programmed to capture usage data in addition to the participant survey responses. The metadata act as a time capsule that shows the most popular questions at each point in time. The analysis of these metadata enable developers to improve the AVA to meet future needs and allow advisors to know which topics are most of interest to students at different points in the semester.

**Participants’ Interaction with the AVA**

The AVA served one of the four fundamental purposes of a text-based artificially intelligent chatbot by providing information-seeking participants with results (Rubin et al., 2010). Research question 2 provided understanding of how participants interacted with the chatbot. Over half of the study's 226 participants interacted with the AVA more than once. Dash et al. (2019) highlighted a chatbot's ability to extend an organization's resources effectively. The AVA chatbot's interaction with participants served as an extension of the honors college's advising office, though there were both successes and challenges in interaction with student participants. There are several reasons for this variation:
1. Participants posed complex questions. For example, “Hello AVA, I have completed my global experience, but I do not see it registering on my honor support was completed.” This question could not be efficiently answered by the chatbot because of the way the question was phrased and the difficulty the AVA had matching this question to any of its programmed intents.

2. Participants posed vague questions, such as, "What financial aid opportunities are there?" The AVA could not provide a response due to the broad nature of this question and the lack of context regarding financial aid opportunities, which could apply to tuition, study abroad funding, or something else entirely.

3. Question phrasing is naturally varied. The request, “I have a new Honors advisor and I'm not sure who it is," was difficult for the AVA to answer, but it could complete a request to schedule an appointment with an advisor. The researcher believes that if the participant had asked, "Who is my advisor," they would have received the answer they were looking for.

4. Participants sometimes used the AVA as a search engine. The idea behind the AVA chatbot was to have a conversation, not to simply serve as a search engine or filter, but the larger goal was to provide participants with a response. The AVA compensated for not having answers by asking participants to clarify or restate the question, which led to many participants shortening their question to keywords, similar to utilizing a search engine. This resulted in some accuracy problems (see number 5).

5. Many questions that were identified as keyword searches did not yield appropriate responses. The AVA responses were geared specifically toward programs within the honors college. Because of this type of inherent limitation, it was unsurprising that
keyword searches were less effective when using the AVA. For example, "The requirements for bachelor of science" did not yield a response at all, while, "My requirement" did yield an answer from the AVA, but the response could not be personalized to the student. Ultimately, keyword searches yielded a slightly lower accuracy rate than the average. The complexities of human language and natural language processing of our framework may have been to blame (Rubin et al., 2010).

In terms of meeting students' needs, participant questions illustrated that the AVA was primarily used to answer basic prescriptive advising related questions. The analysis of participants' questions led to the need to properly categorize the types of questions asked. Categorization of questions was challenging due to varied phrasing from participants. After organizing the questions into categories, frequency of questions was next examined. One of the anticipated benefits of the AVA chatbot was that it would be beneficial for answering repetitive questions. The repetitive frequency of specific questions illustrated that this was indeed an observed benefit of the AVA chatbot. For example, the question "who is my advisor?" was asked 84 different times in four different ways ("Who is my honors advisor?" "Who's my advisor?" "Who is my advisors?" "Who is major advisor?"). The final example was difficult to answer because the application did not have assigned major advisor information in its knowledge database.

TAM Survey Findings

The TAM results addressed the third research question by evaluating participant interaction based on their perceptions towards the AVA chatbot. The TAM survey results were encouraging because they went beyond the AVA metadata and provided participants an
opportunity to share feedback about their experiences using the chatbot. In each of the three TAM survey categories: perceived ease-of-use, perceived usefulness, and intention to use, participants indicated positive intentions towards use of the AVA. The results indicated that the AVA chatbot was easy to use, and that both learning and understanding the chatbot were also easy. The overall 6.16 score in the perceived ease of use questions category supported the goal of this intervention.

The study aimed for the design of the AVA chatbot to be familiar to similar chatbot software. An unintended result was the differences between female and male perceived ease of use. It was difficult to tell why males rated the chatbot lower than females without a quantitative analysis. Males rated the perceived ease of use category of questions lower than females. Data showed 6.31 for females and 5.58 for males on a 7-point Likert scale. There were not enough males who participated in taking the TAM survey to identify a pattern between male respondents.

Since the respondents were overwhelmingly female, it was necessary to further sort the respondents by admission cohort. Between the four admission cohorts represented by both males and females, the Fall 2019 cohort was the largest by far. This was consistent with the AVA chatbot data. Each cohort answered survey questions differently, which evidences their progress in their academic journey. The Fall 2018 cohort consistently rated questions in the perceived usefulness category higher than the other four cohorts. In comparison, the Fall 2020 cohort consistently rated their experience responses within this category the lowest out of the four cohorts. The difficulties of 2020 are well documented and Fall 2020 semester was a challenging semester for all college students, especially Fall 2020 cohort members starting their first semester on campus. Having to rely so much on virtual tools and not having access to face-to-
face resources made the semester more difficult for new students. Their experiences with navigating college resources online may have resulted in online resource fatigue which caused their experience with the AVA chatbot to be negatively perceived.

The two questions in the final TAM survey category, “intention to use,” were the lowest rated on average throughout the survey. The question that stated “I plan to use the AVA chatbot for my advising questions” was the lowest scored question in the entire survey. Results showed a 5.14, the lowest in this category and in the survey overall. These results were consistent among gender but varied among the specific admission cohorts. Even students who rated the AVA positively scored this particular question lower than others. While the data measured general perceptions regarding intention to use the AVA, determining what caused this category to be the lowest was difficult to determine. Study participants may have answered this question with the concern that the AVA would replace their academic advisor instead of be an additional resource.

Some participants rated the AVA lower because they found the chatbot difficult to use. Their negative experiences with the AVA were likely a result of receiving incorrect answers or being issued no answer when the data was not programmed or available. A small number of participants still gave the AVA low ratings despite receiving correct answers, offering no direct correlation to their experience. There could have been several reasons for this; one might be that the participant preferred to speak to advisors in person and not use virtual advising tools or that using the AVA took too long and it was more useful to write an email. In a pandemic-laden semester, virtual fatigue may have impacted participants’ experience with yet another virtual tool. Despite these lower ratings, overall the AVA was still positively rated overall on the seven-point Likert scale. The majority of participants reported a positive experience with the AVA and overall at least somewhat agree that they intend to use the AVA again in the future.
Question 4 underscores how the AVA addresses prescriptive advising questions. The AVA’s success is defined as a chatbot’s ability to deliver advising information and grow organizational resources beyond the office (Dash et al., 2019). The AVA data collected during the first deployment of the chatbot was a good starting point and indicated several areas of success. With only 545 "intents" (programmed responses), AVA's implementation shows just how the chatbot extended existing advising resources. While it is challenging to train and implement an extensive and comprehensive chatbot dataset, the data show that the AVA’s first deployment was successful in meeting the student need for more access to prescriptive advising information (Kader & Woods, 2015).

Before determining whether the AVA chatbot successfully addressed prescriptive advising questions, it was crucial to look at the participants who used the AVA. Walsh (2010) stated that honors students run into similar challenges as non-honors peers, making the honors students an appropriate test population. The results indicated that honors participants had many questions regarding academic advising-related topics and were as concerned about satisfying honors requirements as they were university requirements. The AVA chatbot also highlights the need to prompt more male interaction. Finding out what their needs are and how best to support their needs can be drawn from further analysis of their questions. The AVA can also improve both the student experience and advising outcomes through timely outreach. The AVA should also be a tool to understand student demographics better. The results indicated that the chatbot successfully delivered prescriptive advising information and that information was well received by study participants.

The prescriptive advising strategy should never be used in isolation, but is very well-suited for chatbot technology. Harris (2016) stated that the prescriptive advising approach is
centered around an advisor prescribing a plan. This strategy is similar to chatbot interaction design, where a knowledge database maps words into the most appropriate intent (Abdul-Kader & Woods, 2015). Chatbots operate in an authoritative manner because the software application is programmed with a large capacity for knowing more than participants. This concept of authoritative manner is also in line with the prescriptive approach discussed in this study (Walters, 2016).

Currently, higher education institutions have added challenges due to COVID-related budget reductions. Students also face new realities regarding social isolation and an increased reliance on online resources. Establishing relationships with institutional representatives and peers has a great impact on persistence (Vianden & Barlow, 2015), and the effect of the challenges to students’ ability to do so in fall 2020 remain to be seen. In a post-pandemic setting, providing students with timely access to necessary information through an AI chatbot should not only be convenient but also optimize in-person advising appointments to allow for more meaningful interactions. Academic advisors are tasked with providing students with information about institutional policies and accurate information regarding their academic path (CAS Standard, 2018). These advising tasks are prescriptive and can quickly be delivered by an automated system, such as an AI-chatbot. There is great value in finding ways to implement chatbot technologies into information delivery tasks, however chatbot software is not meant to replace existing personnel. The chatbots are best utilized in a supportive culture that embraces an environment where chatbot technologies are used. It is worth restating that chatbots are intended to provide performance efficiencies and workflow efficiencies when accessing information, not to replace staff.
Limitations

This study was limited to high-achieving, undergraduate honors students. The first phase of the AVA chatbot development was focused on frequently asked questions such as, “Who is my academic advisor?” and, “How do I apply for education abroad scholarships?” The data acquired from the AVA and TAM survey captured participant perceptions and accuracy of the application. It was expected that the small development team size could increase the time needed to publish new design iterations in response to survey feedback, which impacted the overall data collected on improved AVA chatbot features. Funding was also a limitation because staff needed to be hired to program the software and develop new features. Maintenance and ongoing application updates also required a financial commitment by the institution. There were some technical limitations that were not identified until after the study began. One such limitation was that the AVA would sometimes automatically time out and disconnect from its knowledge database. Another limitation was the number of TAM survey participants due to the study’s sample size. However, the TAM sample size was an accurate representation of the total 226 AVA participants. It is important to stress the impact of the COVID-19 pandemic on the overall study. Not being able to establish in-person relationships with students made it difficult for advisors to recommend and encourage use of the AVA chatbot. The researcher also highlights students' fatigue with online resources in general during this unique period of time.

Implication of the Findings

During the organizational analysis, the HPT model provided a workflow for understanding the honors college's values, mission, and vision. The design and development of the AVA chatbot as an intervention tool was born from the original organizational goals of providing meaningful and timely access to advising information to support student academic
progress. The sharing of real-time data with stakeholders and decisionmakers is a benefit to students' wellbeing and offers a better understanding of their needs. Resources such as the AVA can highlight the needs of current and prospective students through conversational analysis. A significant implication of the findings is the value-added real-time data generated by the AVA chatbot.

During the planning of this study, the main benefit of an academic advising chatbot was projected to be increasing students’ access to advising information. While the AVA did provide that additional venue for students to find information on demand, it also yielded another, unintended advantage in providing real-time data about students’ needs to the advising department. Based on the number of questions received about the honors global experience requirement, the participating department increased marketing for students interested in satisfying their global experience requirement. The AVA data was essential at identifying this need and the AVA chatbot offered this insight to department stakeholders. The AVA data trends helped advisors anticipate what students needed without the use of predictive analytics models. Data clarified how advisors can better support their student populations. Ultimately, the AVA chatbot solution helped advising and administrative professionals rethink which resources to highlight for students and how they share these with students.

**Recommendations for Further Research**

More research is needed to understand how to better design and implement knowledge databases for chatbots. Creating effective chatbot solutions requires a comprehensive approach to initial chatbot interface design and developing the specific knowledge database. The more useful and robust the database, the better the chatbot can handle complex queries. Chatbot implementation can be challenging, and a clear strategy for developing additional software
intents is necessary. Research focused on evaluating chatbot application usage as part of a campus deployment is needed. There is also a need for a mixed methods research narrative where academic advisors' and participants' experiences are captured. Adding advisor voices and feedback helps strengthen the case that AVA chatbot usage benefits academic advisor workflows. Research is also needed to effectively evaluate personalized chatbot solutions and how these types of chatbots will affect future design and implementation.

**Conclusion**

Advising departments are always in search of practical tools to streamline information distribution. As advanced technology software makes its way into more academic advising departments, great interest is placed on utilizing these tools to address departmental performance gaps. CAS stated that technology used as part of advising should enhance academic advising services (2018). Chatbot technologies are proven tools that simulate a conversation between a user and a computer (Ghose & Barua, 2013). Participants found the AVA capable of providing accurate answers to their advising questions and the majority of participants had successful conversations that resulted in timely access to advising-related information. Implementing the AVA chatbot within the honors student portal was essential to positioning the AVA in front of honors students. This placement resulted in more students utilizing the chatbot. Both the AVA data and participant TAM survey results support the claim that the AVA’s implementation was a success in the participating honors college.

Although the study takes place within an honors college, it is important to note that the study's findings can be extrapolated to other populations beyond honors. The honors students demand excellence and require services at a high level of developmental advising (Kaczvinsky, 2007). However, the descriptive data from the TAM survey captured as part of the study was not
generalizable and could not be inferred to other populations on campus. The critical values behind chatbot efficiency, information delivery, and data generation are relevant to chatbot implementation on a college campus at large. Chatbots are also well positioned to help administrators gain insight into student behaviors throughout various stages of their academic journey.

Radziwill and Benton (2017) reported the value in chatbots serving as a cost-effective software solution to addressing needs. Chatbots contribute a large amount of data that can provide valuable insight into student trends while also highlighting institutional opportunities. The AVA chatbot was no exception. The AVA data successfully showed where the information gaps existed and what kinds of questions students were asking at different points on their academic journey. Additionally, the AVA data provides helpful insights about participants that can enhance the AVA chatbot and student portal site. Extracted AVA data allowed for more targeted communication to address previously unidentified student needs. The data also showed which student populations feel more supported by the AVA through their successful interaction with the chatbot. The AVA chatbot data illustrate opportunities for improvement to all stakeholders and show paths to addressing the performance gaps. Chatbots could help large and small higher education institutions effectively support their student populations by tracking and measuring overall contributions, as well as pinpointing data insights in real-time.
REFERENCES


Ghose, S., & Barua, J. J. (2013). Toward the implementation of a topic specific dialogue based natural language chatbot as an undergraduate advisor. *In 2013 International Conference on Informatics, Electronics and Vision (ICIEV) (pp. 1-5).* IEEE.


DOI:10.1016/j.chb.2014.07.044


APPENDIX 1:

TECHNOLOGY ASSESSMENT MODEL (TAM) SURVEY

Perceived ease of use: 4 items (1, 2, 3, 4)
Perceived usefulness: 7 items (5, 6, 7, 8, 9, 10, 11)
Intention to use: 2 items (12, 13)

All items will be answered on a seven-point scale ranging from 7-Likert scale:
(1) strongly disagree, (2) disagree, (3) somewhat disagree, (4) neither agree or disagree, (5) somewhat agree, (6) agree, and (7) strongly agree

Reference:

Conceptual definitions:
“The Technology Acceptance Model (TAM)” is the most widely used innovation adoption model. This model has been used in a variety of studies to explore the factors affecting individual’s use of new technology.

“Perceived ease of use” is defined as the degree to which a person believes that using a particular system would be free of effort, which is an imminent acceptance driver of new technology-based applications.

“Perceived usefulness” is a key determinant of intention, which encourages users to adopt more innovative and user-friendly technologies.

“Intention to use” is defined as the likelihood that an individual will use new technology. Intention plays a critical role in the actual use of a new technology.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived ease of use</td>
<td>1. AVA chatbot is easy to use</td>
</tr>
<tr>
<td></td>
<td>2. Learning to use the AVA chatbot is easy for me</td>
</tr>
<tr>
<td></td>
<td>3. AVA chatbot is easy to understand</td>
</tr>
<tr>
<td></td>
<td>4. AVA chatbot is convenient</td>
</tr>
<tr>
<td>Perceived usefulness</td>
<td>5. AVA chatbot helps to save time</td>
</tr>
<tr>
<td></td>
<td>6. AVA chatbot requires minimal effort</td>
</tr>
<tr>
<td></td>
<td>7. AVA chatbot helps me to be self-reliant</td>
</tr>
<tr>
<td></td>
<td>8. AVA chatbot helps to improve my knowledge</td>
</tr>
<tr>
<td></td>
<td>9. AVA chatbot helps to improve my performance</td>
</tr>
<tr>
<td></td>
<td>10. AVA chatbot is effective</td>
</tr>
<tr>
<td></td>
<td>11. AVA chatbot is efficient</td>
</tr>
<tr>
<td>Intention to use</td>
<td>12. I plan to use the AVA chatbot for my advising questions</td>
</tr>
<tr>
<td></td>
<td>13. I am more likely to use the AVA chatbot over a search engine to find answers about academic requirements in the future.</td>
</tr>
</tbody>
</table>
APPENDIX 2:

HONORS PORTAL LANDING PAGE

Figure 1A. Honors Portal Landing Page
APPENDIX 3:

AVA CHATBOT DIALOGUE

Figure 2 A. AVA Chatbot Dialogue
APPENDIX 4:

INITIAL AVA CONCEPTUAL DESIGN

Figure 3A. Initial AVA Conceptual Design
APPENDIX 5:

ITERATIVE AVA CHATBOT DESIGNED

Figure 4 A. Iterative AVA Chatbot Designed

Iterative AVA Chatbot Designed as an Embedded Feature within the Honors Portal

Figure 4 B. Iterative AVA Chatbot Designed as an Embedded Feature
APPENDIX 6:
IRB APPROVAL LETTER

UNIVERSITY of
SOUTH FLORIDA

NOT HUMAN SUBJECTS RESEARCH DETERMINATION

Dear Mr. Lucien:

On 7/5/2020, the IRB reviewed the following protocol:

<table>
<thead>
<tr>
<th>IRB ID:</th>
<th>STUDY000995</th>
</tr>
</thead>
<tbody>
<tr>
<td>Title:</td>
<td>Design, Development, and Evaluation of an Artificial Intelligence Enabled Chatbot for Honors College Student Advising in Higher Education</td>
</tr>
</tbody>
</table>

The IRB determined that the proposed activity does not constitute research involving human subjects as defined by DHHS and FDA regulations.

IRB review and approval is not required. This determination applies only to the activities described in the IRB submission. If changes are made and there are questions about whether those activities constitute human subjects research, please submit a new application to the IRB for a determination.

While not requiring IRB approval and oversight, your project activities should be conducted in a manner that is consistent with the ethical principles of your profession. If this project is program evaluation or quality improvement, do not refer to the project as research and do not include the assigned IRB ID or IRB contact information in the consent document or any resulting publications or presentations.

Sincerely,

Various Monet
IRB Research Compliance Administrator

Institutional Review Boards / Research Integrity & Compliance
FWA No. 00001688
University of South Florida / 3702 Spectrum Blvd., Suite 165 / Tampa, FL 33612 / 813-974-5538

Figure 6 A. IRB Approval Letter
## APPENDIX 7

### PARTICIPANT SAMPLE QUESTIONS A

<table>
<thead>
<tr>
<th>Question</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>How many volunteer hours are necessary?</td>
<td></td>
</tr>
<tr>
<td>How do I see Honors requirements?</td>
<td></td>
</tr>
<tr>
<td>Hello</td>
<td></td>
</tr>
<tr>
<td>Thanks AVA</td>
<td></td>
</tr>
<tr>
<td>advising appointments</td>
<td></td>
</tr>
<tr>
<td>academic completion requirements</td>
<td></td>
</tr>
<tr>
<td>two</td>
<td></td>
</tr>
<tr>
<td>global experiences</td>
<td></td>
</tr>
<tr>
<td>continuing</td>
<td></td>
</tr>
<tr>
<td>community service hours</td>
<td></td>
</tr>
<tr>
<td>community service</td>
<td></td>
</tr>
<tr>
<td>volunteer committee</td>
<td></td>
</tr>
<tr>
<td>upcoming events committee meetings</td>
<td></td>
</tr>
<tr>
<td>upcoming MPR committee meetings</td>
<td></td>
</tr>
<tr>
<td>what</td>
<td></td>
</tr>
<tr>
<td>mpr meeting</td>
<td></td>
</tr>
<tr>
<td>meetings</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Who is my advisor</td>
<td></td>
</tr>
<tr>
<td>how are you today</td>
<td></td>
</tr>
<tr>
<td>who are you?</td>
<td></td>
</tr>
<tr>
<td>no</td>
<td></td>
</tr>
<tr>
<td>who is my advisor?</td>
<td></td>
</tr>
<tr>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>one</td>
<td></td>
</tr>
<tr>
<td>Tell me about global experiences</td>
<td></td>
</tr>
<tr>
<td>Transfer student</td>
<td></td>
</tr>
<tr>
<td>What is needed to graduate with honors distinction?</td>
<td></td>
</tr>
<tr>
<td>Did I fulfill all my requirements?</td>
<td></td>
</tr>
<tr>
<td>advisors</td>
<td></td>
</tr>
<tr>
<td>Clubs</td>
<td></td>
</tr>
<tr>
<td>Mail</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Champs</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>dining hall</td>
<td></td>
</tr>
<tr>
<td>On campus eating facilities</td>
<td></td>
</tr>
<tr>
<td>Food services</td>
<td></td>
</tr>
<tr>
<td>Tutoring</td>
<td></td>
</tr>
<tr>
<td>Travel scholarships</td>
<td></td>
</tr>
<tr>
<td>What scholarships do I qualify for?</td>
<td></td>
</tr>
<tr>
<td>Hey! How many hours of community service do i need to have completed</td>
<td></td>
</tr>
<tr>
<td>Academic</td>
<td></td>
</tr>
<tr>
<td>How can I make an appointment?</td>
<td></td>
</tr>
<tr>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Honors college community service course</td>
<td></td>
</tr>
<tr>
<td>Do I qualify for any scholarships to study abroad?</td>
<td></td>
</tr>
</tbody>
</table>

**Figure 7 A. Participant Sample Questions A**
PARTICIPANT SAMPLE QUESTIONS B

How can I find internships for the summer
thanks
How do I access the honors lounge
Where is the honors college located
What are the hours of the honors college
honors scholarships
Can I apply for a scholarship?
Honors study abroad
Can I study abroad?
What are some study abroad opportunities?
No
Hi, who is my advisor?
Yes
What are the requirements for the honor college
Hello!
No
Where can I find an advisor?
What are some ideas for community service?
Where can I get an internship?
Where is the counseling center
What are the four research tracks
honors scholarships
where can I apply for scholarships
when is the honors college open
how can I get involved in research
who is my advisor
Does the Honors College have their own tutoring?
tutoring?
interest in research
honors courses available for spring 2021
honors international trip
how to register for the global experience studio in spring 2021
global experience studio spring 2021
global experience studio class
foreign language requirement
more options
one
global experience
yes
one
two
What can I do to fulfill my global student requirement?
HIP points
what are HIP points?
where can I find community service opportunities?
what's up
no
who is my advisor

Figure 7 B. Participant Sample Questions B
PARTICIPANT SAMPLE QUESTIONS C

what advisor would i have in the honors college if i am a psychology major
Who is on the dev team for AVA?
Where can I study abroad with the honors college?
When is the new honors college building being built?
Upcoming events in my major
What events are coming up?
Where can I log community service hours
Yes
Where can I study abroad?
Yes
One
What are some global experiences available now?
Continuing
What are my graduation requirements?
Who is my advisor?
What honors events are there this semester?
I am a junior. What honors classes do I have to take
I am a junior
but I am not a first year?
what honors classes do I have left to take?
not now
who is my advisor?
Who is my advisor?
thank you
no
during
Can you tell me more about the community service requirement?
What volunteering opportunities are there?
Is there a minimum GPA to remain in the Honors College?
what is the minimum GPA for honors college
first time in college
What are the Honors College requirements?
Who is my advisor?
Yes
thanks
yes
no
Where can I find the honors college community service canvas course
first year
thank you
no
during
How many volunteer hours do I need?
How do I log in my volunteer hours?
yes please
How do I register an appointment with my honors advisor
Hi I was wondering how to schedule an appointment with my honors advisor
How do I get tutoring?

Figure 7 C. Participant Sample Questions C
PARTICIPANT SAMPLE QUESTIONS D

honors scholarships
honors scholarships
yes
one
global experience
give me more information on global experiences
Give me more information on global experience opportunities
What are the study abroad opportunities?
Who is my academic advisor?
who is my honors advisor
drop in advising
Drop in
yes
one
how to satisfy global experience
when are walk ins for mr lucien
How to schedule advising appointment
how do I get global experience without studying abroad?
what are the research tracks
honors global experience requirements?
honors global experience
counseling resources
getting an internship
internship resources
Where is the USF Counseling Center located?
Honors scholarships
when would I get my scholarship money after completing one of the forms
yes
Scholarships for travel abroad
Scholarships
Once I finish this semester with German 2, will part of my Global Experience requirement be automatic?
yes
global experience
Hello, I am finding it hard to complete my Global Experience Requirement for graduation due to the COVID
do I need to graduate in 4 years
Can I graduate in 5 years
Who is over BS/MD?
major-specific events?
general
What Honors events are coming up?
Am I finished with my honors coursework?
What is my graduation progress?
two
What can I do to satisfy my global experience requirement?
How do I complete my global experience requirement?
FTIC
after fall 2019

Figure 7 D. Participant Sample Questions D
PARTICIPANT SAMPLE QUESTIONS E

How many community service hours do I need to complete?
Yes
What is an LLC?
Where do I schedule a walk-in appointment?
How can I make walk-in appointment?
Who is my advisor?
What are honors classes like?
How are honors classes?
Yes
One
Options for global experience
No
More options
Two
Global Experience
can I take idh3400-005?
can non honors students take honors courses?
who can take medical humanities in a global context pathway courses?
medical humanities in a global context pathway courses
medical humanities in a global context pathway
Can anyone take idh 3400?
Can I take idh3400-005 if I am not in the medical humanities in a global context pathway?
can students who are not part of the medical humanities pathway take courses from that pathway?
global requirements
global citizen project
counseling location
USF Counseling center location?
WHERE is the USF Counseling center?
Where is the USF Counseling center?
Where is the USF Counseling center?
What are the honors research tracks
What 3 resources do you recommend for internships
Where is the USF Counseling center?

Figure 7 E. Participant Sample Questions E