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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON UNIVERSITY MAJOR SELECTION

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ABSTRACT

This research investigation assesses how Artificial Intelligence (AI) influences the decision-making processes of university students in selecting both their field of study and major. With the advancements in AI technology, the field of education has also seen the integration of AI-driven tools and systems designed to assist students in making informed decisions about their academic and career paths. This study aims to explore how recommendation systems, personalized career guidance and data-driven insights influenced by AI impact students' decision making.

In conducting this research, we employ a multifaceted approach, gathering data through surveys, and a thorough analysis of the extant literature. By immersing ourselves in students' experiences and perspectives, our primary goal is to gain insights into the effectiveness of AI in enhancing decision-making processes. Our aim extends to explore both the advantages and challenges linked to the utilization of AI, while also gauging its influence on students' overall satisfaction and confidence in their chosen majors.

Furthermore, our research examines the considerations surrounding the use of AI in decision- making while also investigating biases that may arise within AI algorithms. By addressing these concerns, our study strives to provide insights and recommendations for enhancing AI systems and ensuring fair and transparent decision-making processes for students.

The outcomes of this study will enhance our comprehension of the intersection between AI and education. Offering valuable insights for educators, policymakers, and AI developers, it seeks to elucidate the effective utilization of AI in aiding students' decision-making processes related to their majors. This, in consequence, elevates the success rate, engagement levels, and overall satisfaction of students throughout their academic journeys.

Keywords: Artificial Intelligence, University Major, Recommendation Systems, Personalized Career Guidance.

1. INTRODUCTION

Artificial Intelligence (AI) is making waves across various industries, and its potential impact on education is attracting significant attention. One area of particular interest is how AI can assist students in making decisions about their majors at the university level. With the growing number of educational options available, students often face the challenge of choosing the most suitable

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path. AI-powered tools and systems offer promising solutions to support students in making informed decisions.

The purpose of this research is to explore how AI affects students' decision-making processes when it comes to choosing their majors. By leveraging AI technologies such as recommendation systems, personalized career guidance, and data-driven insights, students can receive tailored support and guidance throughout their decision-making journey. This study aims to investigate the effectiveness of AI-driven tools in facilitating the decision-making process, examine potential benefits and challenges associated with their implementation, and assess their impact on students' overall satisfaction and confidence in their chosen majors.

Throughout this research, we will investigate several studies that have explored the role of AI in assisting students with their major selection. Bellon et al. (2019) conducted an experiment on recommender systems in higher education, finding that AI-support positively influenced students' major selection. Huang et al. (2018) explored the potential of AI in providing personalized career recommendations based on individual and contextual factors. Han & Jo (2021) designed and evaluated a personalized recommendation system for university major selection using machine learning techniques. Chen et al. (2019) developed an intelligent career recommendation system for university students, showcasing how AI can match students' interests, skills, and aspirations with suitable majors. Alzaid et al. (2020) investigated students' perceptions of chatbot-based academic advisors and highlighted the value of AI in delivering personalized support and information to aid decision-making.

The use of AI-driven tools in the decision-making process raises ethical considerations. Cornwall, J. et al. (2023) discussed the ethical challenges surrounding AI in career development, emphasizing the need for fairness, transparency, and bias mitigation. Additionally, Cox, A. M., et al. (2019) explored emerging AI technologies in academic libraries and highlighted the importance of ethical considerations in their implementation.

The impact of AI on students' decision-making processes is not without challenges. Researchers conducted field tests in an attempt to enhance autonomous career decision-making through digital guidance, uncovering challenges related to the interpretation of AI-generated recommendations and the balance between autonomy and support. Portugal, I. et al. (2018) investigated the potential of machine learning algorithms in recommendation systems for e-learning courses, emphasizing the importance of accurate data and algorithmic transparency.

Furthermore, research has addressed students' perceptions and experiences with AI-based solutions. Dawodi, M., Wada, T., & Baktash, J. (2019) examined an intelligent recommender system for academic majors and found positive student feedback regarding the system's usefulness and relevance.

Overall, the extant literature highlights the promising potential of AI in supporting students' decision-making processes in selecting their majors. It underscores the importance of AI-driven recommendation systems, personalized career guidance, and ethical considerations in enhancing decision-making outcomes and ensuring fairness and transparency. However, challenges related to interpretation, bias mitigation, and striking the right balance between autonomy and support need further exploration.

As we delve into this research, we will also explore ethical considerations surrounding the use of AI in decision-making. It is essential to address potential biases that may arise in AI algorithms

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and ensure fairness and transparency in the decision-making processes for students. By examining these ethical aspects, this study aims to provide valuable insights for educators, policymakers, and AI developers to enhance the design and implementation of AI systems in supporting students' major selection.

In conclusion, the integration of AI in students' decision-making processes has the potential to revolutionize the way students approach major selection at the university level. This research study seeks to investigate the impact of AI-driven tools, systems, and approaches on students' decision-making processes, addressing both the benefits and challenges associated with their implementation. By understanding the implications and exploring ethical considerations, this research aims to contribute to the existing body of knowledge on the intersection of AI and education, ultimately improving the support and guidance available to students in their academic and career journeys.

2. LITERATURE REVIEW

2.1 History, Origin, and Usage of Recommendation Systems

Recommendation systems play a crucial role in today's digital landscape, aiding users in navigating the overwhelming amount of information and content available. These systems leverage data and algorithms to provide personalized suggestions, making them indispensable for various industries, from e-commerce to entertainment and education.

Exploring the transformative influence of recommendation systems, a prominent application of AI, this literature review delves into their history, origins, and varied applications. By shedding light on the evolution and significance of recommendation systems in modern digital ecosystems, the review comprehensively examines their development. Additionally, the literature will scrutinize the evolution, types, challenges, and impact of recommendation systems, providing valuable insights into their significance across diverse domains.

2.2 Evolution of Recommendation Systems

Recommendation systems have evolved from simple content-based approaches to complex AI-driven algorithms that consider user behavior, preferences, and contextual information. Early systems relied on content similarity to make recommendations (Lops et al., 2011). However, the beginning of collaborative filtering introduced a game-changing approach by analyzing users' interactions and leveraging collective preferences (Resnick & Varian, 1997). With the rise of AI and machine learning, hybrid systems integrating content-based and collaborative filtering methods gained prominence (Burke, 2007).

2.3 Early Beginnings and Emergence

The roots of recommendation systems trace back to the late 20th century. The MovieLens project, initiated in the late 1990s, pioneered collaborative filtering techniques by soliciting user ratings to suggest movies (Resnick & Varian, 1997). However, the concept of suggesting items based on user behavior and preferences has earlier origins in the library systems that recommended books to readers (Markey, 1999). As technology advanced, web-based recommendation systems began emerging, with Amazon's book recommendations standing out as an early example (Linden et al., 2003).

2.4 Types of Recommendation Systems

Over time, recommendation systems have evolved, offering various approaches tailored to different contexts, such as: Collaborative Filtering recommends items based on users' past behaviors and similarities with other users (Sarwar et al., 2001). Moreover, Collaborative Filtering systems recommend items based on user interactions and preferences (Sarwar et al., 2001). This approach led to the development of user-based and item-based Collaborative Filtering methods. It can be user-based (finding similar users) or item-based (finding similar items).

In content-based filtering, the content-based systems recommend items based on their attributes and users' historical preferences to generate recommendations (Pazzani & Billsus, 2007). They are effective for dealing with the "cold start" problem where limited user data is available. In matrix factorization, the matrix factorization techniques, such as Singular Value Decomposition (SVD) and Alternating Least Squares (ALS), decompose user-item interaction matrices to extract latent factors (Koren et al., 2009). In hybrid recommendation, the hybrid systems combine multiple recommendation techniques to overcome limitations of individual methods, enhancing recommendation accuracy (Adomavicius & Tuzhilin, 2005).

2.5 Diverse Applications

Recommendation systems have found applications in a wide range of industries, such as:

E-Commerce, where platforms like Amazon and eBay employ recommendation systems to suggest products, driving sales and enhancing user experience (Linden et al., 2003). In Entertainment, services like Netflix and Spotify use recommendation systems to curate content, keeping users engaged and satisfied (Lü et al., 2012). In Social Media, social networks such as Facebook and LinkedIn leverage recommendation systems to connect users with relevant contacts and content (Bakshy et al., 2012). In the education sector, recommendation systems aid in suggesting courses, learning resources, and personalized learning paths, enhancing student engagement and outcomes (Ullrich et al., 2018). In content consumption, platforms like YouTube and Spotify employ recommendation systems to curate content tailored to users' preferences, driving longer engagement. Finally, healthcare systems utilize recommendation systems for personalized treatment plans and drug prescriptions (Gong et al., 2021).

2.6 Challenges and Advancements

While recommendation systems offer personalized experiences, they encounter many challenges, such as: Data sparsity, where collaborative filtering systems face data sparsity issues, particularly for new items or users (Koren, 2008). For cold start problem, new users or items lack sufficient data for effective recommendations, necessitating content-based approaches (Adomavicius & Tuzhilin, 2005). Scalability: As user bases grow, scalability becomes a challenge for real-time recommendations (Li et al., 2017). Ethical Concerns: recommendations can inadvertently amplify biases present in the data, necessitating efforts to ensure fairness and diversity (Ekstrand et al., 2018). Advancements in AI, Deep learning, and Natural Language Processing have fueled the development of more sophisticated recommendation algorithms, striving to overcome these challenges.

2.7 Future Directions and Ethical Considerations

As recommendation systems continue to evolve, addressing ethical considerations is paramount.

Ensuring transparency, privacy, and fairness in recommendations is critical to prevent unintended consequences and biases (Lü et al., 2015). Efforts to enhance interpretability and user control over recommendations are gaining attention (Abdollahi et al., 2017).

2.8 The Role of Guidance Counselors

Guidance counselors have played a pivotal role in providing personalized career guidance. Throughout the 20th century, counseling services in educational settings expanded, aiming to assist students in understanding their interests, strengths, and values (Zytowski, 2008). These counselors employed assessments and interviews to guide students toward suitable career paths, fostering a connection between education and workforce needs.

2.9 Technological Advancements and Digital Solutions

With the advent of technology, personalized career guidance transitioned into digital platforms and software applications. The integration of computer-based assessments and databases allowed for more efficient and accurate career matching (Hollands & Toms, 2001). The development of web-based platforms expanded the reach of personalized guidance beyond traditional counseling offices.

2.10 Diverse Applications and Tools

Personalized Career Guidance encompasses various tools and approaches, such as:
Interest Inventories, where interest-based assessments, such as the Strong Interest Inventory, help individuals explore their preferences and identify potential career paths (Donnay & Barnette, 2014). In skills assessments, evaluating individuals' skills and strengths assists in matching them with careers that align with their abilities (Niles & Harris-Bowlsbey, 2017). In personality assessments, tools like the Myers-Briggs Type Indicator (MBTI) aid in understanding personality traits and their relevance to different careers (Pittenger, 1993). In online platforms, modern platforms like LinkedIn offer personalized career recommendations based on users' profiles, connections, and industry trends (Korn, 2021).

2.11 Education and Workforce Development

Personalized career guidance has far-reaching implications for education and workforce development. For example, in Higher Education, educational institutions utilize personalized guidance to help students select majors, courses, and internships that align with their career aspirations (Ullrich et al., 2018). In Workforce Transition, personalized guidance supports individuals transitioning between careers, enabling them to identify transferable skills and explore new opportunities (Sturges et al., 2015). In Professional Development, in the corporate world, organizations provide personalized career development plans to employees, fostering engagement and retention (Lyons et al., 2017).

2.12 Conclusion

Recommendation systems have undergone a remarkable evolution, offering tailored experiences across diverse domains. The evolution of recommendation systems reflects the increasing importance of personalized user experiences in the digital age. As these systems continue to evolve, addressing challenges related to data sparsity, scalability, and ethical concerns becomes essential. From early collaborative filtering methods to complex AI-driven algorithms, recommendation systems have found applications in diverse domains, enhancing engagement, sales, and learning outcomes. The impact of recommendation systems on user engagement, sales, learning, and even healthcare underscores their significance in modern digital ecosystems. As we navigate the future of AI, continued research and ethical considerations will shape the trajectory of recommendation systems, ensuring they contribute positively to users' lives. As industries integrate AI and data-driven approaches further, recommendation systems will remain integral to enhancing user experiences and delivering personalized content and services.

3. METHODOLOGY

For the subject of AI in helping students select their major at the university, a recommended hypothesis is proposed to be: The integration of AI-driven recommendation systems in the university's major selection process will significantly improve students' decision-making, leading to higher satisfaction, increased academic performance, and decreased major-switching rates.

This hypothesis suggests that implementing AI-based recommendation systems will have a positive impact on students' decision-making processes when choosing their major, resulting in improved outcomes and reduced uncertainty in their academic journey.

Based on the hypothesis mentioned earlier, here are some research questions that can be explored:

1. How does the integration of AI-driven recommendation systems impact students' decision-making processes when selecting their major at the university?
2. What are the specific factors that contribute to the effectiveness of AI-based recommendation systems in assisting students with major selection?
3. How do students perceive and evaluate the recommendations provided by AI-driven systems in comparison to traditional methods of major selection guidance?
4. What is the relationship between students' satisfaction with the major selection process facilitated by AI recommendation systems and their subsequent academic performance?
5. Do AI-driven recommendation systems contribute to a reduction in major-switching rates among university students?
6. What are the potential challenges and limitations of implementing AI-based recommendation systems for major selection, and how can they be addressed?

These research questions aim to investigate the impact, effectiveness, perception, outcomes, and challenges associated with the use of AI-driven recommendation systems in the context of helping students select their major at the university.

This study is carried out in Lebanon, with a particular focus on university students. Data is collected using random sampling and a total of 100 questionnaires were received, with 84 of the 100 questionnaires valid. The 16 unreturned questionnaires were excluded from this analysis.

The data is obtained by sending a standardized questionnaire using Google Form, composed of two parts. The first part includes demographic information about the respondent, such as age, gender, academic year, and field of study.

The second part is about using AI and it identifies the types of AI-driven tools used by students, if any. It also measures the participants satisfaction from using the AI-Driven systems. To what extent the AI-driven systems assisted the students to select their major of study.

The questions in the second part were 13, including 9 close-ended questions based on true or false

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or five-point Likert-type scale questions, and 4 open-ended questions to identify any concerns or opinions from the participants.

4. FINDINGS AND RESULTS

The dataset underwent rigorous statistical analysis, employing a diverse array of statistical methodologies to extract meaningful insights from the acquired data. Before initiating the statistical analysis, a meticulous examination was conducted to identify and address any missing values. This proactive step ensured the integrity of the dataset, paving the way for a comprehensive and accurate interpretation of the findings. The incorporation of various statistical approaches not only enriched the depth of analysis but also contributed to a more nuanced understanding of the dataset's intricacies.

Although gender was not a factor in this study, 69% of the respondents were males, while 31% were females. The investigation involved a sample size to variable number ratio of 30:1, with a total of 84 questionnaires in the survey. The subsequent phase included the consideration of dependent and independent variables, as outlined in Table 1. Cronbach's alpha was employed to assess the internal consistency of each variable in the study, revealing a high level of internal consistency with a value greater than 0.7 (0.991).

Table 2 presented the results of the ANOVA test, indicating a very small significance value (sig = 0.000) below the 0.05 level of significance. The calculated F-value of 38.569 was sufficiently large, suggesting relevance between the values. Moving to Table 3, the Kaiser-Meyer-Olkin (KMO) value was determined to be 0.909, exceeding the threshold of 0.5. The Bartlett significance test was also applied, and the values for each variable were less than 0.5. Furthermore, the extracted total variance test yielded a value of 74.68%, surpassing the 60% benchmark.

Table 1

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.912	.911	9

Table 2

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		708.136	67	10.569		
Within People	Between Items	287.000	8	35.875	38.569	.000
	Residual	498.556	536	.930		
	Total	785.556	544	1.444		
Total		1493.691	611	2.445		

Grand Mean = 1.24

Table 3

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.909
Bartlett's Test of Sphericity	Approx. Chi-Square	637.493
	df	28
	Sig.	.000

Participants were found to be from different academic backgrounds, Freshman, Sophomore, Junior, Senior, Graduate and Post Graduate students. The students represented different majors, Business such as Marketing, HR, Management, Hospitality, Computer Science, Engineering, Graphic Design, Pharmacy, and other.

When participants were asked if they had ever utilized any AI-powered tools or systems to assist them in their university major selection process, the majority of respondents (51%) affirmed using some form of AI for assistance. Regarding the type of system used, 35.7% mentioned Chatbots, 15.5% mentioned recommendation systems, and 14.3% mentioned career guidance platforms; the remaining respondents did not use any AI tools.

When participants were asked about their satisfaction with the usage of AI systems to select their university major, 38% of them did not use any AI, while 54% expressed satisfaction ranging from satisfied to very satisfied, and the rest reported a neutral stance.

For those participants who used AI, when asked if the AI-powered tools or systems provided relevant and accurate recommendations for selecting a major, 79.3% of the 51% who utilized AI answered affirmatively.

When participants who used AI were asked how AI-powered tools or systems impacted their decision-making process for selecting a major, the majority of responses indicated that the tools were very helpful, effective, provided an overview, and so on.
Participants who used AI were also asked if they felt that the AI-powered tools or systems understood their unique interests, skills, and aspirations when recommending majors, and 80% responded positively. When respondents who used AI were questioned about the extent to which AI-powered tools or systems assisted them in making an informed decision about their major, 60% provided positive answers.
Regarding confidence in the major chosen with the assistance of AI-powered tools or systems, more than 55% expressed confidence. When asked about how they would rate the usefulness of AI-powered tools or systems in the major selection process, more than 60% confirmed that they found it useful.
Moreover, when respondents were asked whether they would recommend the use of AI-powered tools or systems to other students for major selection, 75% responded affirmatively.

Exploring the difficulties and limitations faced by individuals who use AI powered tools or systems for selection as well as their concerns and reservations about this application revealed additional insightful responses. Apart from the aspect that a significant part of the participants feedback emphasized ethical considerations related to incorporating artificial intelligence into major selection processes.
One common theme among the participants' answers was their apprehension regarding data security and privacy. Many expressed concerns about the vulnerabilities and risks associated with handling personal information in AI driven systems. Worries about access, data breaches and the misuse of sensitive information were prevalent highlighting the crucial need for robust security measures in AI applications for major selection.
Furthermore, accuracy emerged as an ethical concern. Participants raised questions about how reliable AI algorithms in accurately assessing and matching individuals with suitable majors. The possibility of biases within these algorithms and the consequences of recommendations became points of ethical debate. This highlights why ongoing scrutiny and refinement of AI algorithms are necessary to ensure unbiased outcomes in major selection processes.

Additionally, participants also voiced reservations, about losing a touch in the major selection process from an ethical perspective.
There have been concerns raised about how AI driven decision-making could become detached and impersonal possibly overlooking the details of individual experiences, aspirations and potential. This ethical concern highlights the need to strike a balance, between progress and a human centered approach, ensuring that the application of AI in major selection respects the human element and fosters a holistic understanding of each candidate.

5.CONCLUSION

Personalized career guidance has evolved from its early roots in vocational counseling to digital platforms that leverage technology for tailored career recommendation. It has become a vital resource for individuals navigating education and the workforce. As technology advances, addressing ethical concerns, ensuring accuracy, and fostering a holistic approach to career exploration will continue to shape the landscape of personalized career guidance.

The analysis of participants representing diverse academic backgrounds and majors reveals a noteworthy adoption of AI-powered tools in the university major selection process. The majority of respondents, constituting 51%, acknowledged utilizing some form of AI assistance, with notable preferences for Chatbots (35.7%), recommendation systems (15.5%), and career guidance platforms (14.3%). This indicates a growing reliance on technological solutions for navigating the complex decision-making involved in selecting a major.

The participants' responses not only shed light on technical challenges but also underscored the ethical considerations inherent in the integration of AI in major selection processes. Addressing issues related to data security, privacy, accuracy, and preserving the human touch becomes imperative in designing ethical and effective AI applications for this critical aspect of academic and career development.

Examining participants' satisfaction with AI systems for major selection, 54% expressed satisfaction ranging from satisfied to very satisfied. This positive sentiment underscores the perceived effectiveness of AI tools in facilitating informed decisions regarding university majors. Moreover, when evaluating the accuracy and relevance of AI-powered recommendations, a substantial 79.3% of those who utilized AI affirmed their confidence in the reliability of these suggestions, reflecting the potential impact of AI in enhancing decision-making processes.

Notably, participants using AI reported that the tools were not only effective but also understood their unique interests, skills, and aspirations. This sentiment was echoed by 80% of respondents, highlighting the capacity of AI-powered systems to personalize recommendations. Additionally, more than half of the participants expressed confidence in their chosen majors with the aid of AI, further emphasizing the positive role of these tools in fostering assurance in decision-making.

The findings collectively suggest a promising landscape for the integration of AI in university major selection processes, as evidenced by the high level of satisfaction, confidence, and positive recommendations among participants. As technology continues to play a pivotal role in shaping educational experiences, the positive reception of AI tools in this context opens avenues for further exploration and implementation in academic decision-making processes.

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