Paper ID #40917

Progressive Insights in use of Machine Learning to Support Student Engagement Diversity: The XYZ EduOwl chatbot

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Progressive Insights in use of Machine Learning to Support Student Engagement Diversity: The XYZ EduOwl chatbot

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Abstract
Personalized education emphasizes adapting educational content, engagement, and assessment wants to individual learners, departing from traditional, uniform educational models. The manuscript emphasizes the necessity of rethinking curriculum design and assessment methods to align with personalized learning. Traditional curricula and one-size-fits-all assessments may not effectively address diverse learning styles and wants. XYZ EduOwl is a tool developed to address the diverse engagement types and assessment wants of students in the modern educational landscape. It leverages machine learning techniques to identify and cater to individual styles and wants. As a work-in-progress, a simulated dataset generated using ChatGPT ADA was employed to evaluate the validation method of user perceptions of the tool through a comprehensive survey designed to gather insights into user experiences and perceptions. The manuscript explores generating normal distribution plots for each survey question, enabling a visual representation of response trends and variations. Additionally, network analysis was utilized to explore the interconnections among different aspects of user experience - educational interests (X series), engagement styles (Y series), and assessment wants (Z series). The study plans to evolve from theoretical underpinnings to practical application, incorporating extensive data and analysis from a case study conducted at Kennesaw State University. This case study will utilize a variety of courses and departments to gather substantial empirical evidence, demonstrating the tool's effectiveness in catering to individual learning styles and needs. Key findings include visual representations of user response trends through normal distribution plots and network analysis of the interconnections between educational interests, engagement styles, and assessment preferences. The manuscript highlights the crucial role of AI-driven personalization in contemporary education, supported by anonymized data and source code availability for broader academic adoption and validation.

Keywords:
Student Diversity Analysis; Machine Learning in Education; Engagement Spectrum Identification; Personalized Educational

What is Personalized education/ Pedagogical Approaches?

Personalized education represents a paradigm shift in the educational landscape, focusing on tailoring learning experiences to cater to the unique needs, abilities, and interests of each student (see Table 1). This approach, as expounded in Tetzlaff et al. [1] dynamic framework, emphasizes adapting educational content, pace, and methodologies to individual learners. It marks a departure from traditional, uniform educational models, aiming to provide more nuanced and effective instruction that resonates with each student's learning style and pace. In the context of educational equity, Dumont and Ready [2] explore the promise of personalized learning. Their research suggests that such tailored educational approaches could play a crucial role in bridging gaps in educational outcomes among diverse student populations. By acknowledging and addressing the varying backgrounds, skills, and learning wants of students, personalized education can potentially mitigate disparities caused by socioeconomic factors, cultural differences, and varying levels of prior knowledge. Jach et al. [3] delve deeper into the role of personality in education. Their work suggests that an understanding of individual personality traits is essential for the effectiveness of personalized learning strategies. This perspective highlights the need for educators to consider psychological and cognitive factors when developing personalized educational methods. It also underscores the importance of emotional intelligence, motivation, and individual learning wants in shaping educational experiences.

The role of technology in facilitating personalized education, especially in response to the challenges posed by the COVID-19 pandemic, is a critical area of exploration. Tzavara et al. [4] examine the use of "e-me," a personal learning environment, to illustrate how digital tools can support personalized learning experiences both within and outside traditional classroom settings. This study showcases the potential of technology in creating adaptive learning environments that can cater to individual learning paths, track progress, and provide feedback tailored to each student's needs.

Personalized education also necessitates a rethinking of curriculum design and assessment methods. Traditional curricula, which often follow a linear and standardized format, may not align well with the principles of personalized learning. Instead, curricula need to be flexible, allowing for differentiation and adaptation based on individual learner profiles. Similarly, assessment methods in personalized education must move beyond one-size-fits-all approaches, focusing instead on measuring individual progress and mastery of skills in a way that reflects each student's unique learning journey. Moreover, the role of educators in a personalized learning environment shifts from being mere providers of knowledge to facilitators of learning. Educators must possess a deep understanding of their students, be adept at using technology to support learning, and be skilled in creating adaptive learning experiences that cater to diverse learning styles and needs.

What is Learning Styles/ Learner-Centered Strategies?

Learning styles are an integral concept in modern educational theory and practice, encapsulating the diverse and individualized ways in which people absorb, process, and retain information. The extensive body of academic literature, particularly in the realms of e-learning and adaptive learning systems, provides a nuanced understanding of learning styles, especially when viewed through the lens of advanced techniques like machine learning and deep learning. Lester et al. [5] highlight the importance of analytics in education, emphasizing how understanding learning behaviors and wants, which are pivotal elements of learning styles, can be enhanced through data analysis. This approach empowers educators to customize their teaching methods to align with various learning styles, thereby augmenting the efficacy of educational delivery (see Table 1).

Indeed, tailoring education and assessment to each student's needs, particularly within the constraints of limited resources and the necessity to uphold consistent standards, is a complex challenge. However, it is not insurmountable. One approach is leveraging technology to create adaptive learning systems. These systems can personalize content and assessments based on individual learning styles and progress, efficiently using available resources. Moreover, by setting clear learning objectives and standardizing assessment criteria, we can ensure consistency in educational standards. Collaboration between educators, administrators, and technology experts is crucial to develop scalable solutions that balance customization with resource limitations. Additionally, continuous professional development for educators in personalized teaching methodologies can enhance their capability to meet diverse student needs within existing frameworks.

Romero and Ventura's [6] exploration of educational data mining delves into how mining techniques can uncover patterns in learning behaviors, an essential step in identifying diverse learning styles. This understanding is vital for grasping how students interact with educational content and determining the most effective approaches to facilitate their learning. Similarly, Markowska-Kaczmar et al. [7] focus on the personalization of e-learning systems using intelligent techniques. Their work suggests that e-learning platforms, when designed to adapt to individual learning styles, offer a more personalized and consequently more effective learning experience. This adaptability ensures that each student is engaged in a manner most conducive to their learning process. Furthermore, El Aissaoui et al. [8] investigate the use of a hybrid machine learning approach to predict learning styles in adaptive e-learning systems. Their research underscores the role of advanced technology in comprehending and adapting to various learning styles, showcasing how machine learning algorithms can be employed to heighten the adaptability of e-learning systems to individual needs. Altamimi et al. [9] apply regression techniques to predict students' learning styles, revealing the complexity and variability inherent in understanding learning wants. This suggests that a nuanced and multifaceted approach is necessary for accurately identifying and responding to different learning styles.
The employment of adaptive Bayesian networks for student modeling, as demonstrated in the studies by Millán et al. [10], Millán et al. [11], are another innovative approaches. These networks assist in tailoring educational content to individual learning styles, facilitating a more effective and personalized learning process. Liz-Domínguez et al. [12] review predictive analysis tools in education, emphasizing their role in discerning and catering to different learning styles, which is crucial for creating a responsive and efficient educational environment. Sáiz-Manzanares et al. [13] investigate the relationship between personalized e-learning and deep learning in higher education. Their study connects the adaptation of learning experiences to individual learning styles with improved deep learning outcomes, suggesting that personalization leads to more profound and enduring learning. Deep learning-based personalization, as discussed in the works of Zhong et al. [14], Mansur et al. [15], and Rosalina and Sen [16] highlights the use of deep learning algorithms to offer personalized learning experiences. These approaches

consider individual learning styles, thus enhancing the capacity of educational systems to deliver content effectively for each learner.

Lastly, Tsiakmaki et al. [17] explore the use of transfer learning from deep neural networks to predict student performance. This method implicitly links to understanding students' learning styles, as performance is often influenced by the alignment of educational content with an individual's needred learning methods. In summary, learning styles are a critical aspect of educational theory and practice, representing the distinct methods through which individuals engage with and assimilate information. The integration of advanced data analytics, machine learning, and deep learning in educational systems has significantly enhanced the understanding of these styles. This technological advancement enables the creation of adaptive and personalized learning experiences, catering to individual wants, and enhancing the overall effectiveness and efficiency of the learning process.

What is Engagement/Technology and Analytics?

Engagement in education, particularly within the realms of online and adaptive learning systems, is a complex and multifaceted concept that encompasses various aspects of a student's interaction with educational content and systems. The referenced studies shed light on how engagement can be understood, measured, and enhanced through the application of machine learning and clustering algorithms (see Table 1).

In the study by Pasina et al. [18], the focus is on clustering students according to their learning styles. Engagement, in this context, is closely related to how educational content and methodologies align with each student's needed way of learning. The rationale is that when teaching methods resonate with a student's learning style, engagement naturally increases. This approach ensures that learning experiences are more effectively tailored to match each student's inclinations and wants, thereby enhancing their active participation and interest in the learning material. Dutt et al. [19] explore the use of clustering algorithms in educational data mining to identify patterns in student learning behaviors and wants. Here, engagement is interpreted through various metrics such as login frequency, time spent on tasks, and interactions with learning resources. This data-driven approach allows educators to discern different levels and forms of engagement, facilitating the creation of more personalized and engaging learning experiences. By understanding these patterns, educational strategies can be adapted to cater to the needs of different learners, thereby maximizing their engagement and potential learning outcomes.

Hybrid machine learning approach is to understand student behaviors in adaptive educational systems. Aissaoui et al. [20] in their study, by clustering learners according to their behavior patterns, found out that it becomes possible to identify different engagement levels and tailor educational interventions accordingly. This approach helps in creating a more dynamic and responsive learning environment that adjusts to the needs and behaviors of individual students. El Aissaoui et al. [21] contribute to this field by using a hybrid machine learning approach to predict learning styles in adaptive e-learning systems. In their perspective, engagement is optimized when the learning environment adapts to diverse learning styles, making the process more intuitive and effective for each student. This adaptability ensures that students are more likely to engage deeply with the content, as it aligns with their natural learning wants and tendencies. Akhuseyinoglu and Brusilovsky [22] highlight the importance of modeling individual differences among learners to predict engagement and success in online learning. Their research suggests that engagement is significantly influenced by how well the learning environment accommodates individual wants, abilities, and challenges. By understanding and addressing these differences, educators can develop more effective strategies to enhance engagement, leading to improved learning outcomes.

In essence, engagement in educational settings is about the depth and effectiveness of student interaction with learning materials and environments. It is influenced by multiple factors, including learning styles, behaviors, individual wants, and the adaptability of the learning system to these factors. By employing data-driven approaches, such as machine learning and clustering algorithms, educators can gain insights into these factors and tailor learning experiences to meet the diverse needs of students. This personalization of the learning process not only makes education more effective but also more enjoyable and relevant for each student, ultimately fostering a more engaged and successful learning journey.

Table 1: Applications Machine Learning Techniques for in Student Diversity Learning

Citation	**C1. Personalized Education/ Pedagogical Approaches**			**C2. Learning Styles/Learner-Centered Strategies and Infrastructure**							**C3. Engagement/Technology and Analytics**						
	C1.1.	C1.2.	C1.3.	C2.1.	C2.2.	C2.3.	C2.4.	C2.5.	C2.6.	C5.1	C3.1.	C3.2.	C3.3.	C3.4.	C3.5.	C3.6.	C3.7.
Tetzlaff, Schmiedek, Brod [1]	▪	▪	▪						▪		▪		▪	▪	▪	▪	▪
Dumont and Ready [2]							▪	▪	▪								
Jach, Bardach, Murayama [3]				▪	▪	▪	▪			▪							
El Aissaoui et al. [8]							▪				▪	▪	▪		▪	▪	▪
Altamimi et al. [9]					▪		▪		▪		▪	▪	▪	▪	▪	▪	▪
Zhong et al. [14]							▪				▪	▪		▪	▪		▪
Mansur et al. [15]												▪	▪	▪	▪	▪	▪
Rosalina & Sen [16]							▪				▪	▪	▪	▪	▪	▪	▪
Tsiakmaki et al. [17]							▪				▪	▪	▪	▪	▪	▪	
Pasina et al. [18]				▪	▪	▪	▪										
Dutt et al. [19]							▪	▪			▪	▪	▪	▪	▪	▪	▪
El Aissaoui et al. [21]				▪	▪	▪	▪				▪	▪	▪	▪	▪	▪	
Akhuseyinoglu and Brusilovsky [22]				▪	▪	▪	▪										

Note:
C1.1. Dynamic Framework, C1.2. Curriculum and Assessment Adaptation, C1.3. Comprehensive Transformation, C2.1. Role of Personality in Learning, C2.2. Learning Style Clustering, C2.3. Predicting Learning Styles, C2.4. Modeling Learners' Individual Differences, C2.5. Educational Equity, C2.6. Promise of Personalized Education, C5.1 Shift in Educator Roles, C3.1. Technology Integration, C3.2. Educational Data Mining, C3.3. Learner Behavior Analysis, C3.4. Hybrid Machine Learning, C3.5. Regression Techniques, C3.6. Deep Learning-Based Personalization, C3.7. Transfer Learning.

XYZ EduOwl Tool Development
The inception of XYZ EduOwl was rooted in the recognition of the diverse learning wants and spectra of students in the modern educational landscape. Traditional teaching methods often fell short in addressing this diversity, leading to a gap in engagement and academic performance. The concept was first implemented in undergraduate courses in Construction Management at Kennesaw State University. The modular educational structure, informed by the insights gathered, showed significant improvements in student engagement, academic performance, and overall satisfaction. With this finding, the team envisioned a tool that could leverage machine learning techniques to identify and cater to these varied learning styles and wants. The tool's (XYZ EduOwl) basic constructs included the students' educational interests (X), engagement spectrums (Y), and assessment wants (Z), allowing educators to design courses that are more aligned with their students' needs.

By analyzing data on student engagement, learning wants, and assessment types, the tool could tailor educational content and teaching methodologies to individual students.Utilizing advanced machine learning algorithms, such as K-means clustering, XYZ EduOwl segments students into distinct groups based on their engagement styles and assessment wants. This segmentation allows for the creation of customized educational modules and teaching strategies.
A major focus of XYZ EduOwl is promoting inclusive education. The tool is adept at identifying and addressing the diverse needs of students, ensuring that education is accessible and effective for all. XYZ EduOwl integrates various tools like browsing capabilities, Python, and DALL-E, enhancing its functionality and providing a comprehensive platform for educational assistance.
In this study:
'Y' (Educational Interests) explored are:
- General Education Courses topics
- Major-Specific Courses topics
- Elective Courses topics
- Beyond Curriculum topics (Career Development, Skills Enhancement, etc.)

'Y' (Engagement Spectrum) explored are:
- Forerunners: Always at the forefront, first to adopt new ideas and technologies.
- Steady Engagers: Consistent and reliable in participation, regularly contributing.
- Gradual Engagers: Initially less engaged, becoming more involved over time.
- Silent Engagers: Quietly engaged, need observation and reflection over vocal participation.
- Unsure Engagers: Show hesitation or uncertainty, need additional support to engage more actively.

'Z' (Assessment Wants) explored are:
- Direct Submission Assessment: For submission assignments that involve submitting work directly, such as assignments, projects, or exams.
- Indirect Submission Assessment: For submission assignments that involve feedback or evaluation from others, like peer reviews or self-evaluations.
- Qualitative Submission Assessment: For submission assignments that involve non-numerical evaluation, focusing on quality of writing, understanding, or creativity.

- Quantitative Submission Assessment: For submission assignments that involve numerical evaluation, such as grades or scores.
- Direct Formative Assessment: Assignments need direct observation and feedback during learning, like quizzes or practical tasks.
- Indirect Formative Assessment: Assignments need gathering information about learning from others, like peer feedback or self-reflection.
- Qualitative Formative Assessment: Assignments need non-numerical feedback during learning to improve understanding and skills.
- Quantitative Formative Assessment: Assignments need numerical feedback during learning, like scores on quizzes.
- Direct Summative Assessment: Direct evaluation at the end of an instructional unit, such as a final project or exam.
- Indirect Summative Assessment: Gathering information at the end of an instructional unit from others, like peer reviews.
- Qualitative Summative Assessment: Non-numerical evaluation at the end of an instructional unit, focusing on the application of learned concepts.
- Quantitative Summative Assessment: Numerical evaluation at the end of an instructional unit, like final grades or scores.

XYZ EduOwl Tool Validation

In order to comprehensively evaluate the user perception of the XYZ EduOwl tool, an innovative approach was employed using ChatGPT, a generative AI language model developed by OpenAI. The model, known as ADA, was instrumental in generating a simulated dataset, which was crucial for our analysis.

With the assistance of ChatGPT ADA, a set of simulated responses was structured to mirror real-world user feedback. This simulation involved creating responses for 100 respondents, encompassing a diverse range of demographic backgrounds and user experiences with XYZ EduOwl. The dataset was meticulously designed to include over 10,000 data points, ensuring a comprehensive representation of potential user perceptions and interactions with the educational tool. The generated data was structured to align with the survey's format, which included multiple-choice questions and rating scales across various dimensions such as demographics, initial use experience, perceptions, expectations, personalization experience, course design wants, overall satisfaction, and factors contributing to successful tool usage.

To ensure the validity and effectiveness of the survey design, a preliminary analysis of the simulated data was conducted. This step was crucial for assessing whether the questionnaire adequately captured the diverse aspects of user experience and perception that the study aimed to investigate. Post-data generation and structuring, advanced statistical methods were employed for in-depth analysis. This included generating normal distribution plots for each survey question, enabling a visual representation of response trends and variations. Additionally, heatmap and network analysis were utilized to explore the interconnections among different aspects of user experience - educational interests (X series), engagement styles (Y series), and assessment wants (Z series).

Survey Design

The use of simulated data, coupled with rigorous analytical methods, served as a validation tool for the survey design. It ensured that the questionnaire was comprehensive, capturing a wide range of user experiences and perceptions, and thus, was well-suited for the intended research purpose. The primary aim of this survey was to gather insights into the demographic profiles, initial use experiences, perceptions, expectations, and personalization experiences of users, primarily students in construction management and architecture at KSU.

The survey on XYZ EduOwl was structured to comprehensively capture user interactions and perceptions. It began with demographics, collecting essential data on participants' backgrounds. The initial use section focused on users' first interactions and potential applications of the tool. We examined users' expectations for learning or research improvements and their likelihood of recommending XYZ EduOwl. Another section explored users' wants regarding XYZ EduOwl's features and desired enhancements. We also gathered insights on users' educational interests, engagement, and assessment wants. Participants expressed their views on integrating XYZ concepts into course design and syllabus updates. Finally, respondents rated their overall satisfaction and identified factors crucial for the tool's successful use, with an open-ended section for additional comments.

DATA ANALYSIS

Normal distribution

Normal distribution analysis is a statistical method used to understand how data points are distributed around a mean or average value. In the context of survey responses normal distribution curves can provide followig valuable insights.

The survey analysis used multiple curves representing diverse respondent groups to understand varying perspectives within the student body. These curves reveal the heterogeneity of opinions, highlighting the necessity for educational features catering to diverse needs. Overlapping curves indicate common views, suggesting shared priorities, while divergent sections reveal differing opinions, essential for tailoring educational strategies. Peaks of curves denote dominant perceptions, offering insights into the general consensus. The curve's width illustrates the range of responses, with wider curves indicating diverse views and narrower ones suggesting agreement. Comparatively analyzing these curves provides valuable insights into the dynamics of different student groups, aiding in more inclusive and effective decision-making.

Through normal distribution analysis, study can gain a deep understanding of student’s needs and wants, facilitating more informed and student-centric approaches in educational tool design and pedagogical planning.

In this study, 28 factors are suitable for such analysis. Figure 1 provides a nuanced understanding of how different groups of students rate the importance of support and training, which can be instrumental in tailoring the tool to meet diverse needs and expectations.

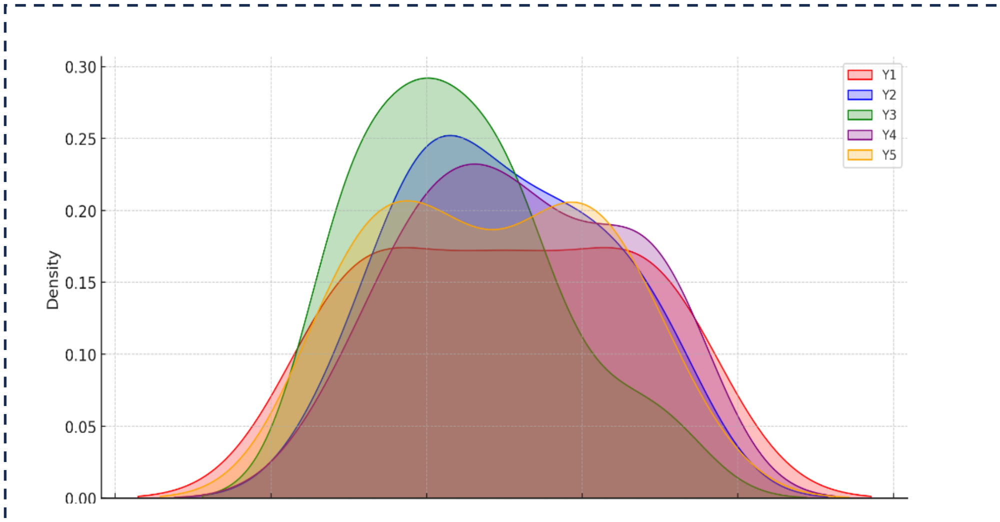

Figure 1: A nuanced understanding of how different groups of students rate the importance of support and training,

Heatmaps
The heatmaps represent the concurrence relationships between different categories of: Educational Interests ('X' series), Engagement Spectrum ('Y' series), and Assessment Wants ('Z' series). In these heatmaps, each cell corresponds to the frequency or strength of the relationship between two categories.

Heatmap of 'X' with 'Y': This heatmap shows the connections between students' educational interests ('X') and their engagement styles ('Y'). By examining which cells are darker (indicating higher values), we can understand which educational interests are most commonly associated with particular engagement styles. For instance, if a cell representing "General Education Courses topics" (an 'X' category) and "Forerunners" (a 'Y' category) is dark, it suggests that students interested in general education topics tend to be early adopters of new ideas and technologies (see Figure 2).

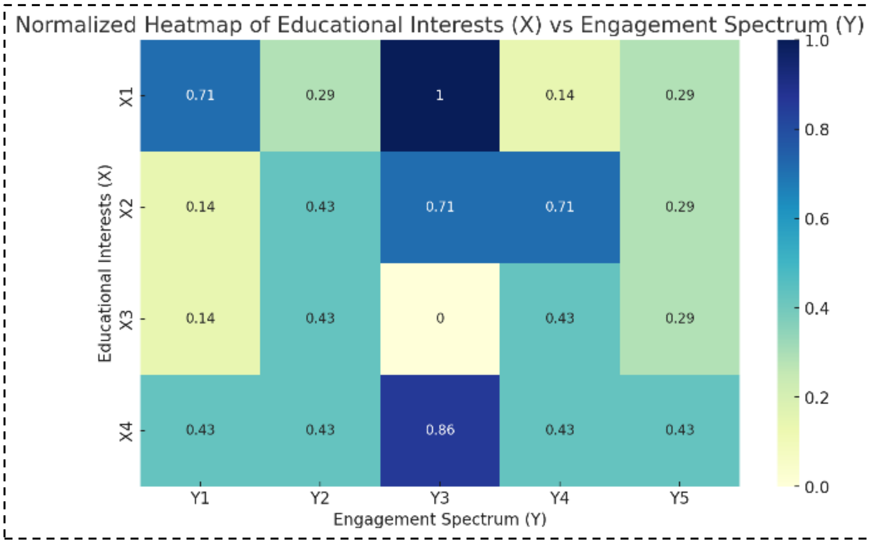

Figure 2: Heatmap of 'X' with 'Y'

Heatmap of 'X' with 'Z': This heatmap illustrates the relationships between students' educational interests ('X') and their assessment wants ('Z'). This can reveal, for example, whether students interested in major-specific courses need certain types of assessments, like project-based evaluations or quizzes. Darker cells indicate a stronger association between a specific educational interest and an assessment want (see Figure 3).

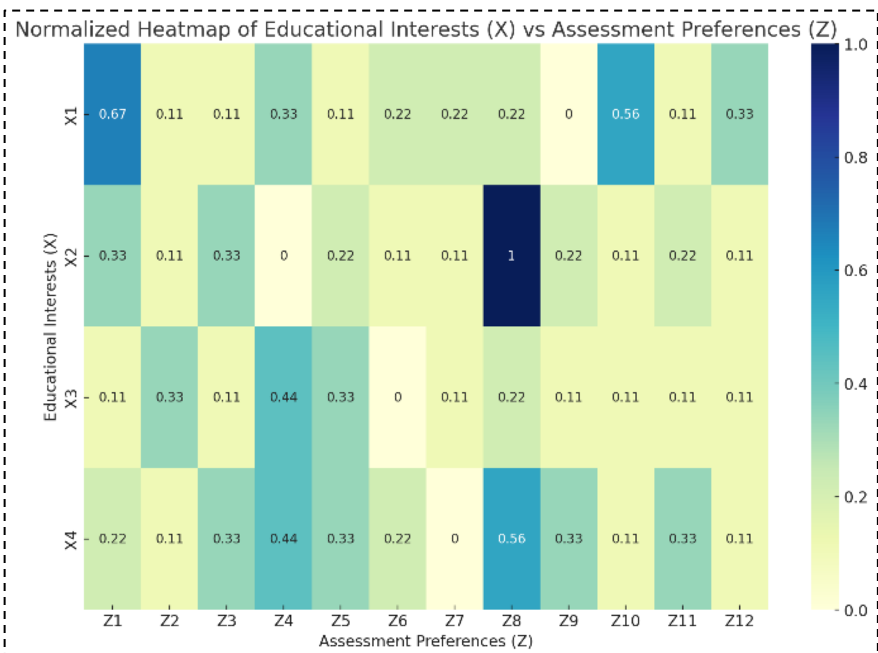

Figure 3: Heatmap of 'X' with 'Z'

Heatmap of 'Y' with 'Z': This heatmap connects students' engagement styles ('Y') with their assessment wants ('Z'). This helps to understand how different types of student engagement correlate with assessment wants. For instance, if students who are "Steady Engagers" show a strong want for qualitative summative assessments, this would be indicated by a darker cell at the intersection of these two categories (see Figure 4).

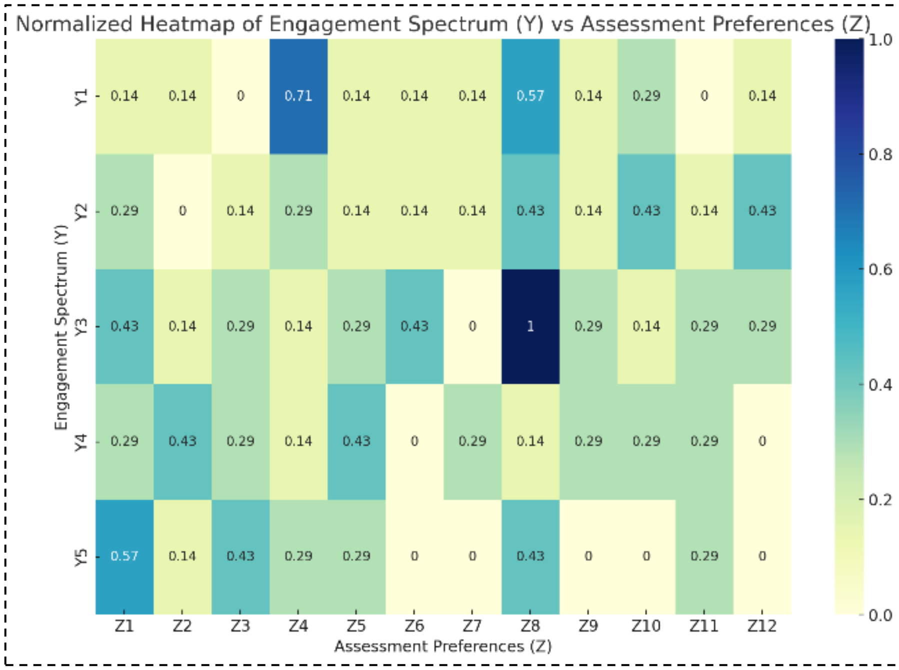

Figure 4: Heatmap of 'Y' with 'Z'

From these heatmaps, you can convey the interconnectedness of students' interests, engagement styles, and assessment wants. They offer a visual representation of the data that can be quickly interpreted to identify patterns and trends. Such insights can be particularly useful in educational planning, helping to tailor teaching methods, course content, and assessment strategies to align with the wants and behaviors of students. For instance, if a strong correlation is found between a certain educational interest and an engagement style, educators can use this information to modify their instructional approaches or materials to better engage students with those interests.

Network visualization

The network visualization (Figure 5) represents the relationships and interactions among three main categories of data: Educational Interests ('X' series), Engagement Spectrum ('Y' series), and Assessment Wants ('Z' series). Each category is represented by a set of nodes, and the connections between these nodes are depicted by edges. The visualization aims to provide insights into how these categories are interrelated based on the survey data from students. Here's a breakdown of what each element in the visualization represents:

There are type of nodes:

- **Red Nodes:** These represent the 'X' series, i.e., the Educational Interests of students. They are located in the innermost circle of the graph.
- **Blue Nodes:** These denote the 'Y' series, i.e., the Engagement Spectrum of students. They form the middle circle.
- **Green Nodes:** These are the 'Z' series, representing students' Assessment Wants. They are positioned in the outermost circle.

The edges (lines connecting the nodes) indicate the relationships between these different categories. In this specific visualization, only significant relationships are shown (edges with a weight greater than 0.4). The color intensity of an edge correlates with its weight (frequency), as derived from the survey data. Darker edges suggest stronger or more frequent connections. These circles help visually organize the nodes into their respective categories and provide a clear distinction between the 'X', 'Y', and 'Z' series.

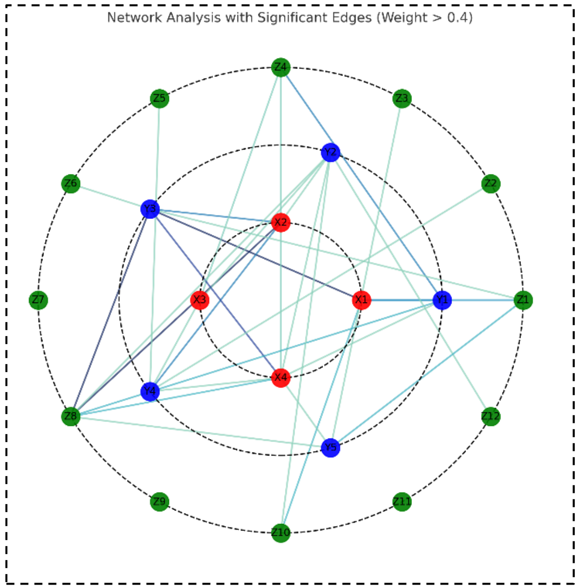

Figure 5: network visualization of relationships and interactions among three main categories of data X, Y, and Z

Network analysis

The network analysis thus visualizes the interconnectedness of students' educational interests, their engagement styles, and their wants for different types of assessments. By focusing on significant edges, the visualization highlights the most prominent or common relationships within the dataset, offering insights into patterns that might be important for educational strategies, course design, and student support systems.

The network analysis (see Table 2) represents a quantitative analysis of the nodes (representing Educational Interests, Engagement Spectrum, and Assessment Wants) in a network graph derived from survey data. The metrics provided in the table — Eigenvector Centrality, Degree Centrality, and Betweenness Centrality — each offer a unique perspective on the roles and importance of these nodes within the network. From the analysis, we can conclude that certain nodes (particularly X1, X2, X4) are highly central, influential, and critical in linking different components of the network. This information can be extremely valuable in understanding how students interact with educational content, their engagement wants, and how they need to be assessed. It can also inform strategies for tool design, learning approaches, and the further development of educational features, ensuring they are aligned with the central interests and wants of the students.

Table 2: The quantitative analysis of the nodes in a network graph derived from survey data.

Node	Eigenvector Centrality	Degree Centrality	Betweenness Centrality
X4	0.283061	0.80	0.060411
X1	0.281144	0.80	0.064684
X2	0.279491	0.80	0.067096
Y2	0.267683	0.75	0.053841
X3	0.261217	0.75	0.057023
Y4	0.256905	0.70	0.040639
Y1	0.251544	0.70	0.045846
Y3	0.248488	0.70	0.046028
Y5	0.214222	0.55	0.017299
Z8	0.205062	0.45	0.007353

Discussion

Personalized education is a comprehensive approach that demands a significant transformation in teaching methodologies, curriculum design, assessment strategies, and the use of technology. It holds the promise of making education more inclusive, equitable, and effective by focusing on the individual learner's journey. As this approach continues to evolve and gain traction, it has the potential to fundamentally reshape the educational landscape, making learning more engaging, relevant, and impactful for each student. On the other hand, learning styles are diverse and multifaceted, representing the unique ways individuals engage with and process information. The integration of advanced data analytics, machine learning, and deep learning in educational systems provides significant insights into these styles, enabling the creation of more adaptive and personalized learning experiences. These technological approaches help educators and learning platforms to cater to individual wants and enhance the overall effectiveness of the learning process. Engagement in educational contexts, especially online and adaptive learning, is about how actively and effectively students interact with learning materials and environments. It is influenced by factors such as learning styles, behaviors, and individual differences. Understanding and enhancing engagement involves using data-driven approaches to tailor learning experiences to meet the diverse needs of students, thereby making learning more personalized, effective, and enjoyable.

Empirical Evidence and Future Research

In our pursuit to extend the boundaries of educational technology research, we are currently advancing towards a practical application of our theoretical concepts. This endeavor involves conducting a small-scale pilot study at Kennesaw State University (KSU), focusing on the utilization of generative AI tools, including the XYZ EduOwl, to create personalized course content. This content is uniquely tailored to the diverse backgrounds and interests of individual students across various departments and colleges, including the College of Architecture and Construction Management, The Southern Polytechnic College of Engineering and Engineering Technology (SPCEET), and Bagwell College of Education at KSU. This ambitious project has already led to the collection of substantial data from different courses taught in these departments. The breadth of data is crucial in achieving more reliable and valuable outcomes, which we aim to detail in our subsequent paper. This practical implementation will facilitate the collection of both pre- and post-intervention data, focusing on aspects such as student engagement, motivation, and performance. Additionally, it will enable us to gather student perspectives on the personalized content through surveys.

Furthermore, understanding the importance of transparency and replicability in research, we have taken the necessary steps to anonymize the data adequately. This anonymized dataset, along with the source code of the XYZ EduOwl tool, will be made available for broader adoption and scrutiny. We believe this openness not only fortifies the credibility of our research but also encourages further exploration and application of AI-driven educational tools in diverse academic settings. This initiative aligns with our commitment to contribute meaningfully to the academic community and to foster innovation in educational technology.

The insights gleaned from this study are expected to shed light on the practical challenges, effectiveness, and student reactions to AI-driven personalization in education. This research will not only validate our theoretical propositions but also pave the way for future explorations in the field of AI-driven educational tools, potentially revolutionizing how educational content is delivered and perceived in diverse learning environments.

Conclusion

This manuscript represents a progressive development of the work-in-progress towards supporting personalized education, a paradigm shift from traditional to tailored learning experiences. The development and ongoing work of the XYZ EduOwl tool underscore a crucial response to the diverse educational needs of today's students. Leveraging advanced machine learning techniques, XYZ EduOwl has the potential to identify and accommodate the varied engagement types and assessment wants that characterize the modern educational landscape.

The innovative use of a simulated dataset generated via ChatGPT ADA for validation purposes marks a novel approach in educational research, blending AI capabilities with traditional survey methods. The insights gleaned from the comprehensive survey, visualized through normal distribution plots, have provided a clear picture of user perceptions and experiences analysis. These visual representations have been instrumental in the future identification of trends and variations in student responses, offering a data-driven foundation for further tool development. Furthermore, the application of network analysis has revealed interconnections among educational interests, engagement styles, and assessment wants, with the capacity to highlight the complex nature of learning experiences. This analytical approach has been explored to facilitate a deeper understanding of how different aspects of the educational experience are interrelated and how they can be better aligned with individual learner needs.

In conclusion, the XYZ EduOwl project, while still a work in progress, has laid down a framework for future advancements in personalized education. The findings of this study not only contribute to the field of educational technology but also pave the way for more nuanced, effective, and student-centered educational practices. As the tool continues to evolve, it will be examined to play a role in shaping a more adaptable, responsive, and inclusive educational landscape.

Lastly, our research at Kennesaw State University is progressing from theory to practice, utilizing AI tools like XYZ EduOwl for personalized education in various departments. Our pilot study is generating significant data to assess student engagement and performance, with the goal of publishing more detailed findings. We prioritize transparency, offering anonymized data and source code for public use, enhancing our research's credibility and fostering AI application in education. This study promises insights into the effectiveness of AI-driven educational personalization and its future potential.

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