



ARTIFICIAL INTELLIGENCE (AI) AND CHATGPT IN LEARNING: ASSESSING EFFECTIVENESS AND OVERCOMING CHALLENGES IN THE AGE OF INDUSTRY 4.0

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ABSTRACT

This research investigates the application of artificial intelligence (AI) in higher education, explicitly evaluating its effectiveness in fostering self-directed learning and self-assessment among university students. The primary objective is to assess how AI can enhance teaching-learning and promote greater learning independence. The study employed data analysis using the Rasch model and examined respondent demographics, with the sample comprising 82% male and 27% female students, predominantly aged 18-23 years. All participants were university students. Findings reveal that AI significantly decreased reliance on human guidance and facilitated increased student independence in learning. The Rasch model analysis highlighted the effectiveness of AI across various levels of learning difficulty, demonstrating its ability to adapt to individual student needs. In summary, AI integration in higher education boosts student independence and adapts to diverse learning challenges, underscoring its value in enhancing educational quality. Consequently, incorporating AI into higher education holds significant promise for advancing self-directed learning and improving academic outcomes.

ABSTRAK

Penelitian ini mengkaji penerapan kecerdasan buatan (AI) dalam pendidikan tinggi, dengan fokus pada efektivitasnya dalam mendukung pembelajaran mandiri dan penilaian diri di kalangan mahasiswa. Tujuan utama penelitian ini adalah untuk mengevaluasi bagaimana AI dapat meningkatkan proses pengajaran-pembelajaran dan mendorong kemandirian belajar di kalangan mahasiswa. Metode yang digunakan adalah analisis data menggunakan model Rasch dan evaluasi demografis responden, yang terdiri dari 82% mahasiswa laki-laki dan 27% mahasiswa perempuan, dengan sebagian besar berusia 18-23 tahun. Semua responden adalah mahasiswa. Hasil penelitian menunjukkan bahwa penggunaan AI secara signifikan mengurangi ketergantungan pada bimbingan manusia dan meningkatkan kemandirian mahasiswa dalam belajar. Analisis Model Rasch menunjukkan distribusi efektivitas penggunaan AI pada berbagai tingkat kesulitan belajar, mencerminkan kemampuan teknologi ini untuk beradaptasi dengan kebutuhan individu mahasiswa. Kesimpulannya, penerapan AI dalam pendidikan tinggi tidak hanya meningkatkan kemandirian mahasiswa tetapi juga dapat beradaptasi dengan berbagai tingkat kebutuhan dan kesulitan belajar, menjadikannya alat yang penting dalam meningkatkan kualitas pendidikan. Dengan demikian, integrasi AI dalam pendidikan tinggi memiliki potensi besar untuk memajukan pembelajaran mandiri dan efektivitas akademik.

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INTRODUCTION

Amidst this ambitious global agenda, artificial intelligence, renowned for its ability to replicate human cognitive functions (Zhou, 2023), has undergone an extraordinary resurgence in recent years. Propelled by groundbreaking advancements in machine learning, natural language processing, computer vision, and robotics, this resurgence has sparked transformative changes across various sectors and redefined social norms. This technological renaissance positions AI as a formidable ally in achieving the SDGs (Ametepey et al., 2024). At the nexus of cutting-edge technology and global sustainability, AI's ability to analyze vast datasets, uncover complex patterns, and generate actionable insights has emerged as a critical mechanism for forging new pathways toward sustainable development.

The integration of AI in education offers several significant advantages, particularly in personalized learning (Niloy et al., 2024), intelligent tutoring systems, and automated assessment. Personalized learning becomes feasible due to AI's ability to assess and address the diverse needs of the entire student population. AI algorithms, such as those based on reinforcement learning, can dynamically evaluate individual student needs and tailor the learning process accordingly (Bulathwela et al., 2024). This individualized approach ensures that each student receives the necessary support and resources for their unique learning journey. Additionally, AI-powered intelligent tutoring systems can interact with students (Niu et al., 2024), providing valuable real-time feedback and guidance, thereby enhancing the overall learning experience.

A significant impact of AI in education is the automation of assessment (Dempere et al., 2023), which combines computer vision and natural language processing systems to grade homework, quizzes, and exams automatically. These automated assessment systems reduce instructors' workload, allowing them to dedicate more time to student engagement and support (Alamäki et al., 2024). Additionally, AI can enhance teacher-student collaboration through various feedback mechanisms and analytical tools. By offering insights and analytics (Demartini et al., 2024), AI helps educators better understand student performance and progress, enabling more effective teaching strategies and fostering a collaborative educational environment (Alsabt et al., 2024). Given the transformative potential of AI in education, it is essential to reflect on its broader implications and explore how this technology can be leveraged to benefit both students and educators.

Although AI has demonstrated great potential in transforming education through personalized learning (Bahroun et al., 2023), the development of intelligent tutoring systems, and automated assessment, there is a lack of research utilizing the Rasch Model to evaluate the impact of AI deeply. The Rasch Model, which provides an objective and measurable analysis of individual abilities and item difficulties, can offer more accurate insights into the effectiveness of AI in enhancing learning outcomes (Hwang, 2022). Currently, most research focuses on the general benefits of AI without thoroughly assessing how this technology affects various aspects of student abilities. By employing the Rasch Model (Hermanto & Miftahuddin, 2021), researchers can precisely measure the extent to which AI meets individual educational needs and improves academic outcomes. Therefore, there is a critical need for studies that integrate the Rasch Model in the evaluation of AI in education to ensure that this technology truly delivers significant and measurable benefits for students and educators.



literature Review

Leveraging Technology to Enhance Teaching

Over the past two decades, the integration of digital tools in educational settings has surged due to various factors, including the increasing availability of these tools and evolving student expectations. Learning Management Systems (LMS) are central to this digital transformation, which have become nearly ubiquitous in secondary and tertiary educational institutions. Versatile LMS platforms serve as comprehensive hubs (Pesovski et al., 2024) for course-related activities, such as facilitating collaboration and discussion through forums and distributing assignments and supplementary materials like self-assessment quizzes and instructional videos. Additionally, LMS platforms have data collection features that record user interaction, allowing educators to monitor student engagement (Salas-Pilco et al., 2022) and identify struggling students early on to provide timely feedback.

Beyond LMS, students have received other technological innovations positively, even if not widely implemented. Examples include using Augmented Reality (AR) in classrooms (Hamal et al., 2022) and AI-powered teaching assistants like Jill Watson from the Georgia Institute of Technology. Integrating such informational tools in education has demonstrated measurable benefits from administrative and academic perspectives, particularly in higher education settings. These advancements highlight the potential of digital tools to enhance educational experiences and outcomes by providing dynamic and interactive learning environments.

ChatGPT

ChatGPT is an AI-based chatbot developed by OpenAI, initially released on November 30, 2022, using GPT-3.5 and subsequently updated on March 14, 2023, with GPT-4. Many consider ChatGPT one of the most powerful AI tools ever created (Kamalov et al., 2023). It is a large language model based on the generative pre-trained transformer (GPT) framework, further refined through supervised learning and reinforcement learning techniques. ChatGPT's ability to understand and respond (Chang et al., 2023) to various questions with a high level of expertise and its capacity to maintain ongoing dialogues with users is highly impressive. The model can perform various tasks, from writing poetry in specific styles and forms to generating computer code (Silva et al., 2024) according to given requirements. While its responses are not always perfect, ChatGPT has achieved unprecedented performance levels. In its latest release based on GPT-4, ChatGPT has demonstrated above-average performance on several standardized tests such as the AP, SAT, LSAT, and GRE. ChatGPT's success has marked a turning point in the adoption of AI in society, including in education, and highlights AI's capabilities while sparking discussions about its future (Kamalov et al., 2023).

Ouyang et al. (2022) analyzed how AI has been integrated into higher education, focusing on research from 2011 to 2020. They highlighted self-assessment and self-directed learning as key motivators influencing attitudes toward AI adoption in academic settings. Their findings underscore AI's transformative potential in promoting more autonomous and proactive learning approaches among students. Additionally, Kim and Bennekin (2016) conducted practical trials involving AI-based platforms designed for academic support (Niloy et al., 2024). Their research revealed a significant reduction in students' reliance on human advisors, indicating a shift towards embracing AI technology for educational purposes. This shift lessens dependence on traditional consultation methods and increases students' enthusiasm and inclination to use AI-based tools and resources. Both studies emphasize AI's



evolving role in reshaping educational dynamics, from enhancing self-directed learning strategies (Chang et al., 2023) to reducing reliance on conventional academic support systems. These insights depict AI's growing acceptance and integration as a catalyst for innovation in higher education practices.

RESEARCH METHODS

This study employs a quantitative approach to analyze the effectiveness and challenges of using Artificial Intelligence (AI) and ChatGPT in education (Jauhiainen & Guerra, 2023) within the context of the Fourth Industrial Revolution. Respondents' answers are quantified on a nominal scale and using Likert-type ratings, with the data processed using Winstep software based on the Rasch Model (Miftahuddin et al., 2020). This method enables structured and precise analysis of the collected data, facilitating an understanding of the impact and acceptance of AI tools like ChatGPT in educational settings. The study aims to provide a clear and objective assessment of AI's role in enhancing learning experiences and outcomes by measuring responses.

The research design is descriptive and aimed at providing a detailed explanation of respondent characteristics and the quality of the statement items developed for each variable. This descriptive analysis is crucial for identifying patterns and trends in how AI and ChatGPT are utilized in educational contexts (Michalon & Camacho-Zuñiga, 2023). By thoroughly depicting these characteristics, the study offers insights into the demographic factors influencing the effectiveness of AI tools in learning environments. The descriptive approach also helps explain the nuances of user interactions with AI, highlighting areas where AI can be most beneficial or where it faces significant challenges.

In processing the data with Winstep software, the study utilizes the Rasch Model to ensure robust analysis (Hermanto & Miftahuddin, 2021). This approach allows for a comprehensive examination of the reliability and validity of the collected data, providing a strong foundation for evaluating the effectiveness of AI and ChatGPT in education. Using the Rasch Model addresses common measurement challenges encountered in educational research, ensuring the findings are accurate and meaningful. By providing detailed and rigorous analysis, this study contributes valuable insights into integrating AI technology in education, highlighting potential benefits and identifying key barriers to effective implementation in the era of the Fourth Industrial Revolution.

Table 1. Questions

Question	Type	Code
Does ChatGPT play an important role in learning	5-point Likert	N1
How would you rate your overall experience of using AI/ChatGPT	5-point Likert	N2
How well you felt you understood the material presented by AI/ChatGPT	5-point Likert	N3
How easy you find it to learn with the features provided by ChatGPT	5-point Likert	N4
You would recommend the use of ChatGPT in learning to your peers	5-point Likert	N5
You would choose ChatGPT as your main tool for learning	5-point Likert	N6

Question	Type	Code
ChatGPT affects your understanding of learning materials	5-point Likert	N7
You would choose ChatGPT as your primary learning tool in the future	5-point Likert	N8
In some situations, ChatGPT can replace the role of the teacher	5-point Likert	N9
Compared to YouTube videos, ChatGPT does not seem to be better than listening to an explanation from a person	5-point Likert	N10
You are tempted to use ChatGPT whenever you need to	5-point Likert	N11
ChatGPT may prevent you from trying to solve problems yourself before asking for help	5-point Likert	N12
AI and ChatGPT may impact the field of education	5-point Likert	N13

Table 1 shows the types of questions used in the survey to evaluate participants' perceptions of ChatGPT's role in learning. All questions in the table use a 5-point Likert scale, allowing respondents to express their level of agreement or disagreement with various statements related to using ChatGPT. These questions cover various aspects such as the importance of ChatGPT in learning, overall experience in using AI/ChatGPT, understanding of material presented by AI, ease of learning with ChatGPT features, and recommendations for its use to others. The questions are designed to gather comprehensive data on participants' perceptions and experiences using ChatGPT as a learning tool.

Furthermore, the table also includes questions that evaluate participants' inclination to use ChatGPT in the future, such as choosing it as the primary learning tool and recommending it to peers. There are also questions addressing the influence of ChatGPT on understanding the material and its role in replacing teachers in certain situations. Additionally, the table encompasses a comparison between ChatGPT and other learning methods, such as YouTube videos, and the potential impact of AI and ChatGPT on education. Using the Likert scale, this research can gain in-depth insights into participants' attitudes, beliefs, and preferences regarding using ChatGPT in the educational context, which is useful for identifying the strengths and weaknesses of AI in learning.

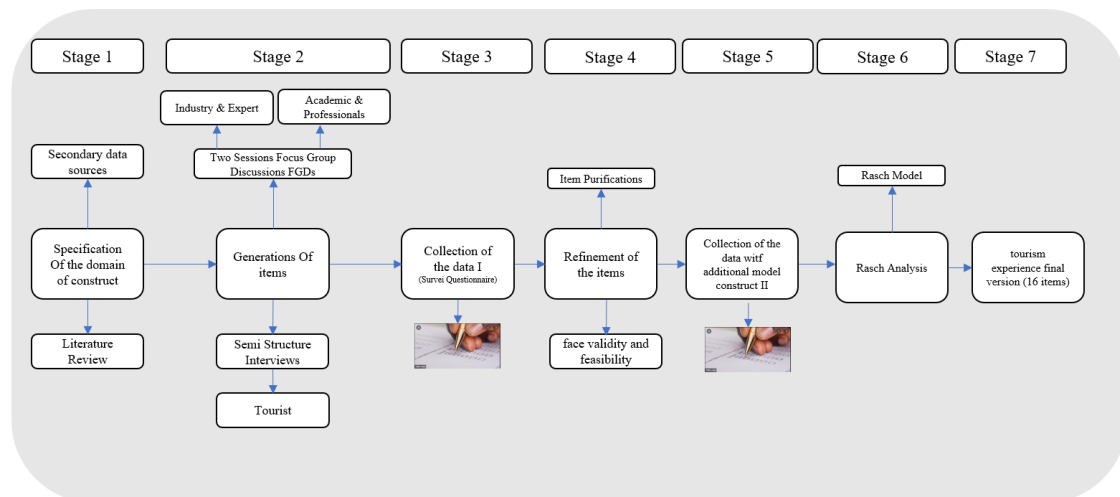


Figure 1. Research Design and Process

Figure 1 illustrates how the researchers employed a systematic and advanced theoretical approach to analyze the data. The method to achieve the report's objectives consists of eight systematic stages. The first stage involves determining the domain and related structure by considering memories related to parental behaviour toward children through a review of previous literature and secondary data. The second stage involves focused group discussions and semi-structured interviews with the community, parents, and experts. The third stage is the implementation of the first survey questionnaire, followed by the fourth stage, which refines the items based on face validity and feasibility. The second survey questionnaire with additional structural design is conducted in the fifth stage. The sixth stage involves Rasch analysis for a comprehensive evaluation of the variables, and finally, the seventh stage establishes the final version of the items.

This method combines literature evaluation, secondary data, interviews, and surveys to identify and validate the domains and structure of respondents' experiences, with Rasch analysis ensuring a robust evaluation. For instance, in the first stage, the researchers meticulously reviewed past literature and secondary data to establish a foundational understanding of the domain and structure related to parental behaviour. This foundational work is crucial as it sets the stage for subsequent stages, ensuring the data collected is relevant and comprehensive.

Overall, the researchers' systematic approach ensures that each stage builds upon the previous one, leading to a well-rounded and validated set of items that accurately measure respondents' experiences. The use of Rasch analysis in the sixth stage is particularly noteworthy as it thoroughly evaluates the variables, ensuring that the final items are both valid and reliable. This meticulous process highlights the importance of a structured approach in research, ensuring that the findings are robust and can be confidently used to inform future studies and interventions.

Table 2 presents the frequency distribution and percentage of research participants based on three demographic variables: gender, age, and occupation. According to the gender data, out of 109 participants, the majority were female, with 82 participants accounting for 75.2%, while male participants numbered 27, or 24.8%. This indicates a significant gender imbalance in this research sample, with females dominating the participant group.

Table 2. The Profile of Research Respondents

Variable	Frequency	Percentage
Gender		
Male	27	24.8%
Female	82	75.2%
Total	109	100%
Age		
15-17	3	2.8%
18-20	56	51.4%
21-23	49	45%
>24	1	1%
Total	109	100%
Job		
Student	109	100%



In the context of age variables, participants were divided into four distinct categories: 15-17 years, 18-20 years, 21-23 years, and over 24 years. The most populous age group was 18-20 years, which included 56 participants, accounting for 51.4% of the total sample size. This was followed by the 21-23 years age group, which comprised 49 participants or 45%. The 15-17 age group was significantly smaller, with only 3 participants (2.8%), and the over 24 age group had a mere 1 participant (0.9%). These figures demonstrate that the majority of participants fell within the typical college-age range.

Furthermore, it is noteworthy that every participant in this study was a student, bringing the total number of participants to 109, which represents 100% of the sample. This comprehensive data underscores the study's primary focus on the student demographic, suggesting that the research is likely centered around issues pertinent to the student population or the educational environment.

RESULTS AND DISCUSSIONS

The findings of this research highlight that AI and ChatGPT have been positively embraced within the educational sphere, with a significant majority of students exhibiting high levels of engagement and satisfaction. The quantitative data collected shows that students perceive the AI-generated content as informative and engaging, indicating that this technology can deliver relevant and useful material supporting their learning journey. This suggests a strong potential for AI tools to attract and sustain student interest in educational activities.

Furthermore, most respondents indicated that AI tools, especially ChatGPT, provide clear explanations and personalized feedback. This capability is particularly beneficial as it aids students in comprehending the material more effectively by offering explanations that cater to their individual learning needs. The application of AI in delivering specific and detailed feedback has been shown to enhance student's understanding of complex subjects, thereby improving the overall quality of their learning experience.

These findings underscore the potential of AI technologies like ChatGPT to significantly contribute to the educational process by fostering greater student engagement and providing tailored support that enhances learning outcomes.

Summary Statistic

Table 3. Summary Statistics of 109 Measured (Extreme and Non-Extreme) Person

	TOTAL SCORE	COUNT	MODEL		INFIT		OUTFIT	
			MEASURE	ERROR	MNSQ	ZSTD	MNSQ	ZSTD
MEAN	48.8	13.0	1.26	.42	0	0	0	0
S.D.	7.3	.0	1.29	.21	0	0	0	0
MAX.	65.0	13.0	6.44	1.84	0	0	0	0
MIN.	28.0	13.0	-1.37	.33	.21	-2.9	.20	-3.0
REAL RMSE .52 TRUE SD 1.18 SEPARATION 2.26 Person RELIABILITY .84								
MODEL RMSE .47 TRUE SD 1.20 SEPERATION 2.54 Person RELIABILITY .87								
S.E. OF Person MEAN = .12								
Person RAW SCORE-TO-MEASURE CORRELATION = .95								
CRONBACH ALPHA (KR-20) Person RAW SCORE "TEST" RELIABILITY = .86								

The analysis of the Rasch model presented in Table 3 provides a detailed assessment of respondent abilities and the reliability of the measurement instrument. The data reveals an average total score of 48.8, indicating an average performance level among the respondents. The mean measure of 1.26 reflects the overall ability level, with a standard deviation of 1.29 indicating a moderate spread of abilities. The maximum score of 65 and the minimum score of 28 highlight the range of performance within the sample. The Infit and Outfit Mean Square (MNSQ) statistics fall within acceptable limits, with a minimum Infit MNSQ of 0.21 and an Outfit MNSQ of 0.20, demonstrating that the responses fit the Rasch model well and ensuring the validity of the measurements.

The reliability of person measures is confirmed through various indices. The Real Root Mean Square Error (RMSE) is 0.52, and the Model RMSE is 0.47, both relatively low, indicating high measurement precision. The true standard deviation (True SD) values of 1.18 (Real) and 1.20 (Model) show that the instrument effectively differentiates between various levels of respondent abilities. The separation indices of 2.26 (Real) and 2.54 (Model), along with person reliability scores of 0.84 (Real) and 0.87 (Model), further reinforce the instrument's capability to distinguish between different performance levels, reflecting the consistency and robustness of the measures.

Additionally, the average person standard error (0.12) indicates the precision of the average measure estimates. The person raw score-to-measure correlation of 0.95 underscores a strong relationship between raw scores and Rasch measures, demonstrating the model's accuracy in reflecting the respondents' true abilities. The Cronbach Alpha (KR-20) value of 0.86 confirms the internal consistency and reliability of the test, indicating that the items consistently measure the same underlying construct. Overall, these results validate the effectiveness of the Rasch model in analyzing data, ensuring reliable and meaningful interpretations of respondent performance.

Rating Scale

Table 4. Rating Scale Summary of Category Structure Model=" R"

CATEGORY		OBSERVED		OBSVD	SAMPLE	INFIT	OUTFIT	ANDRICH THRESHOLD	CATEGORY MEASURE	
LABEL	SCORE	COUNT	%	AVERA	EXPECT	MNSQ	MNSQ			
1	1	32	2	-.70	-.85	1.17	1.27	NONE	(-3.22)	1
2	2	125	9	-.12	-.24	1.12	1.12	-1.91	-1.54	2
3	3	340	24	.32	.47	.89	1.00	-.89	-.19	3
4	4	583	41	1.38	1.32	.86	1.01	.34	1.49	4
5	5	337	24	2.38	2.4	1.00	1.00	2.46	-3.64	5

The Rasch model analysis in Table 4 reveals the performance of the rating scale and its category structure. Each category shows a different distribution of observations, with Category 1 having the lowest number of observations (32, or 2%) and Category 4 having the highest (583, or 41%). The Average Observation (AVRGE) and Expected (EXPECT) values indicate how well the categories reflect the measured ability. For example, Category 1 has an average observation of -0.70 and an expectation of -0.85, indicating that this category reflects lower ability.

The Mean Square (MNSQ) values for Infit and Outfit are used to evaluate the data's fit to the Rasch model. Category 3 shows the best Infit MNSQ of 0.89, while Category 1 has an Infit MNSQ of 1.17 and an Outfit MNSQ of 1.27, which, although still acceptable, indicates



some misfit to the model.

The Andrich Thresholds indicate the transition points between categories, with negative values for lower and positive for higher categories. For example, the threshold for Category 2 is -1.91, suggesting that respondents with an ability around -1.91 are more likely to choose Category 2 over other categories. The increasing Andrich Threshold values from Category 1 to 5 indicate increased measured ability. Category 5 has the highest threshold (2.46), meaning only respondents with the highest ability will likely choose this category.

Overall, this analysis suggests that the rating scale works well in measuring the respondents' abilities, with most categories showing a good fit to the Rasch model.

Unidimensionality

Table 5. Unidimensionality of Standardized Residual Variance (In Eigenvalue Units)

		-- Empirical --			Modeled
Total raw variance in observations	=	198.7	100.00%		100.00%
Raw variance explained by measure	=	91.7	46.10%		45.70%
Raw variance explained by persons	=	41	20.60%		20.40%
Raw variance explained by items	=	50.6	25.50%		25.20%
Raw unexplained variance (total)	=	107	53.90%	100.00%	54.30%
Unexplained variance in 1st contrast	=	23.8	12.0%	22.20%	
Unexplained variance in 2nd contrast	=	14.3	7.2%	13.40%	
Unexplained variance in 3rd contrast	=	13.5	6.8%	12.60%	
Unexplained variance in 4th contrast	=	10.8	5.4%	10.10%	
Unexplained variance in 5th contrast	=	8.9	4.5%	8.30%	

The Rasch model analysis in Table 5 reveals the unidimensionality of standardized residual variance in eigenvalue units. The total raw variance in the observations is 198.7 (100%), of which 91.7 (46.1%) is explained by the measurement model, including variance explained by persons (41 or 20.6%) and items (50.6 or 25.5%). This indicates that the Rasch measurement model can explain nearly half of the total variance in the observations, signifying that the model substantially measures a single dimension of the ability being assessed.

Conversely, 53.9% of the raw variance remains unexplained by the model, indicating significant residual variance. The first contrast of unexplained variance is 23.8 (12.0%), suggesting the potential presence of additional dimensions not captured by the model. The second to fifth contrasts range from 4.5% to 7.2%, which, although lower, still indicate the presence of some variance that the primary dimension cannot explain. However, overall, the model demonstrates that the majority of the variance in the data can be explained by a single primary dimension, with some remaining variance suggesting the possibility of additional factors influencing the outcomes.

Unidimensionality is a fundamental assumption in the Rasch model, which posits that a set of items measures a single construct or ability. In this context, the analysis results show



that the Rasch model successfully explains a substantial portion of the observed variance, though residual variance indicates other influencing factors.

Despite some unexplained variance, the Rasch model demonstrates good capability in measuring the primary dimension of the observed ability. This is crucial for ensuring that the measurement scale used has high validity and reliability in measuring a specific ability.

Item Measure

Table 6. Item Person Statistics: Measure Order

ENTRY	TOTAL	TOTAL		MODEL	INFIT		OUTFIT		PT-MEASURE		EXACT	MATCH	Item
NO	SCORE	COUNT	MEASURE	S.E.	MNSQ	ZSTD	MNSQ	ZSTD	CORR.	EXP.	OBS%	EXP%	
6	337	109	1.18	0.12	0.98	-0.1	0.96	-0.3	0.66	0.65	38.3	45.8	N6
8	357	109	0.89	0.12	0.95	-0.3	0.96	-0.3	0.67	0.64	47.7	46.9	N8
9	366	109	0.76	0.12	1.35	2.4	1.33	2.3	0.61	0.63	38.3	47.1	N9
10	373	109	0.65	0.12	1.5	3.3	1.48	3.2	0.54	0.62	41.1	47.6	N10
12	390	109	0.38	0.13	0.94	-0.4	1.06	0.4	0.62	0.61	61.7	49.5	N12
11	411	109	0.03	0.13	1	0	1.01	0.1	0.62	0.58	55.1	51.7	N11
7	417	109	-0.08	0.13	0.79	-1.5	0.83	-1.2	0.6	0.58	65.4	52.5	N7
3	425	109	-0.23	0.14	0.71	-2.2	0.73	-2.1	0.6	0.57	65.4	52.9	N3
2	433	109	-0.38	0.14	0.67	-2.6	1.1	0.7	0.53	0.56	58.9	53.9	N2
5	433	109	-0.38	0.14	0.99	0	0.99	0	0.62	0.56	52.3	53.9	N5
1	445	109	-0.62	0.14	0.78	-1.6	0.79	-1.5	0.55	0.54	66.4	55	N1
13	464	109	-1.05	0.15	0.98	-0.1	1.2	1.3	0.5	0.51	56.1	58.2	N13
4	468	109	-1.14	0.16	1.04	0.3	1.15	1	0.47	0.5	51.4	58.4	N4
MEAN	409.2	109	0	0.14	0.98	-0.2	1.04	0.3			53.7	51.8	
S.D.	39.9	0	0.71	0.01	0.22	1.6	0.2	1.4			9.6	4	

The Rasch model analysis in Table 6 reveals item and respondent statistics based on the order of item difficulty. The items in the table are arranged from the most difficult to the easiest, with "Item Measure" indicating the difficulty of each item. The average measure value is 0 with a standard deviation of 0.71. The item with the highest total score is N6, with a measure of 1.18, while the item with the lowest total score is N4, with a measure of -1.14. The Standard Error (S.E.) values for all items range between 0.12 and 0.16, indicating reasonably precise estimates of item difficulty.

The Mean-square (MNSQ) values for infit and outfit are mostly around 1, suggesting a good fit to the model. However, some items, such as N9 and N10, have higher MNSQ values, indicating greater variability than expected and the potential presence of anomalies or misfit in responses.

The point-measure correlation (PT-MEASURE CORR) between item scores and individual abilities shows a strong and positive relationship, with an average correlation value of 0.6. This indicates that the items consistently measure the same construct. The exact match percentage between observed and expected results varies, with an average observation of 53.7% and an expectation of 51.8%. Some items, like N1 and N7, show a higher exact match percentage than expected, indicating that these items are easier for respondents than others.

Overall, this analysis demonstrates that the Rasch model provides accurate and consistent measurement in assessing individual abilities based on their responses to these items. However, some items require further attention due to their misfit with the model. This is crucial to ensure that the measurement scale used has high validity and reliability in measuring specific abilities.



Person measure

Table 7. Person measure

ENTRY	TOTAL	TOTAL	MEASURE	MODEL	INFIT		OUTFIT		PT- MEASURE		EXACT	MATCH	
NUMBER	SCORE	COUNT		S.E.	MNSQ	ZSTD	MNSQ	ZSTD	CORR.	EXP.	OBS%	EXP%	Person
5	65	13	6.44	1.84	MAXIMUM MEASURE				0	0	100	100	005PM
68	65	13	6.44	1.84	MAXIMUM MEASURE				0	0	100	100	068LM
16	63	13	4.39	0.77	1.25	0.6	2.38	1.5	-0.43	0.24	84.6	85	016LM
48	63	13	4.39	0.77	2.38	1.8	3.44	2.2	-0.16	0.24	92.3	85	048PM
39	61	13	3.52	0.58	1.03	0.2	1.43	0.9	-0.03	0.32	69.2	70.9	039PM
71	60	13	3.21	0.54	1.34	0.9	1.21	0.6	0.3	0.34	61.5	66.2	071LM
74	60	13	3.21	0.54	1.34	0.9	1.77	1.5	-0.5	0.34	46.2	66.2	074PM
99	60	13	3.21	0.54	1.19	0.6	1.38	0.9	-0.22	0.34	46.2	66.2	099PM
106	60	13	3.21	0.54	0.83	-0.3	0.88	-0.1	0.28	0.34	61.5	66.2	106LM
102	59	13	2.94	0.51	1.69	1.5	1.77	1.6	-0.19	0.36	38.5	63.3	102LM
80	58	13	2.69	0.48	1.08	0.3	1.1	0.4	0.35	0.38	53.8	60.4	080LM
96	58	13	2.69	0.48	1.93	2	2.45	2.7	-0.12	0.38	46.2	60.4	096PM
34	57	13	2.47	0.46	1.78	1.7	1.54	1.3	0.56	0.39	30.8	57.3	034PM
62	57	13	2.47	0.46	1.09	0.4	1.19	0.6	0.16	0.39	38.5	57.3	062PM
94	57	13	2.47	0.46	3.07	3.5	2.71	3.2	0.26	0.39	53.8	57.3	094LM
101	57	13	2.47	0.46	0.52	-1.3	0.53	-1.3	0.5	0.39	69.2	57.3	101PM
43	56	13	2.26	0.45	0.76	-0.5	0.79	-0.5	0.42	0.4	46.2	55.1	043LM
54	56	13	2.26	0.45	0.57	-1.2	0.61	-1	0.66	0.4	61.5	55.1	054LM
83	56	13	2.26	0.45	0.82	-0.4	0.76	-0.6	0.4	0.4	61.5	55.1	083PM
91	56	13	2.26	0.45	1.37	1	1.34	0.9	0.46	0.4	30.8	55.1	091PM
2	55	13	2.07	0.43	2.29	2.5	2.13	2.3	0.41	0.41	30.8	54.3	002PM
6	55	13	2.07	0.43	2.14	2.3	1.99	2.1	0.5	0.41	23.1	54.3	006PM
72	55	13	2.07	0.43	1.78	1.7	1.6	1.4	0.32	0.41	53.8	54.3	072PM
90	55	13	2.07	0.43	1.34	0.9	1.43	1.1	0.06	0.41	46.2	54.3	090PM
19	54	13	1.89	0.42	1.33	0.9	1.22	0.7	0.68	0.42	30.8	54.5	019PM
26	54	13	1.89	0.42	0.53	-1.3	0.54	-1.3	0.74	0.42	69.2	54.5	026PM
44	54	13	1.89	0.42	0.99	0.1	0.95	0	0.76	0.42	38.5	54.5	044PM
88	54	13	1.89	0.42	0.95	0	0.97	0.1	0.3	0.42	53.8	54.5	088PM
89	54	13	1.89	0.42	1.16	0.5	1.04	0.2	0.41	0.42	76.9	54.5	089PM
3	53	13	1.72	0.41	0.77	-0.5	0.8	-0.4	0.62	0.43	69.2	53.4	003PM
4	53	13	1.72	0.41	0.55	-1.2	0.52	-1.4	0.27	0.43	69.2	53.4	004PM
13	53	13	1.72	0.41	0.69	-0.7	0.7	-0.7	0.42	0.43	53.8	53.4	013PM
57	53	13	1.72	0.41	0.72	-0.6	0.69	-0.8	0.37	0.43	69.2	53.4	057PM
85	53	13	1.72	0.41	0.96	0	1.17	0.5	0.1	0.43	61.5	53.4	085PM
105	53	13	1.72	0.41	0.49	-1.4	0.53	-1.3	0.32	0.43	53.8	53.4	105PM
108	53	13	1.72	0.41	0.67	-0.8	0.63	-1	0.71	0.43	69.2	53.4	108PM
51	52	13	1.55	0.4	1.03	0.2	1.15	0.5	0.16	0.44	46.2	51.7	051PM
58	52	13	1.55	0.4	0.24	-2.7	0.24	-2.7	0	0.44	92.3	51.7	058LM
69	52	13	1.55	0.4	0.24	-2.7	0.24	-2.7	0	0.44	92.3	51.7	069PM
86	52	13	1.55	0.4	0.24	-2.7	0.24	-2.7	0	0.44	92.3	51.7	086LM
107	52	13	1.55	0.4	0.24	-2.7	0.24	-2.7	0	0.44	92.3	51.7	107PM
52	51	13	1.39	0.39	0.89	-0.1	0.89	-0.1	0.62	0.44	61.5	51.4	052PM
55	51	13	1.39	0.39	0.98	0.1	0.95	0	0.75	0.44	38.5	51.4	055PM
8	50	13	1.24	0.39	2.16	2.3	2.02	2.1	0.73	0.45	23.1	51.2	008PM
20	50	13	1.24	0.39	0.53	-1.3	0.49	-1.5	0.81	0.45	61.5	51.2	020LM
40	50	13	1.24	0.39	1.19	0.6	1.13	0.5	0.63	0.45	46.2	51.2	040PM
49	50	13	1.24	0.39	0.9	-0.1	0.83	-0.3	0.8	0.45	46.2	51.2	049PM
50	50	13	1.24	0.39	0.21	-2.9	0.2	-3	0.55	0.45	76.9	51.2	050PM
65	50	13	1.24	0.39	1.37	1	1.38	1	-0.27	0.45	53.8	51.2	065PM
1	49	13	1.1	0.38	0.59	-1.1	0.64	-0.9	0.77	0.46	61.5	51.1	001PM
14	49	13	1.1	0.38	0.8	-0.4	0.88	-0.2	0.76	0.46	46.2	51.1	014PM
27	49	13	1.1	0.38	0.34	-2.1	0.38	-2	0.66	0.46	76.9	51.1	027PM
33	49	13	1.1	0.38	1.79	1.7	1.68	1.6	0.52	0.46	30.8	51.1	033PM



ENTRY NUMBER	TOTAL SCORE	TOTAL COUNT	MEASURE	MODEL	INFIT		OUTFIT		PT- MEASURE	EXP.	OBS%	EXP%	Person
				S.E.	MNSQ	ZSTD	MNSQ	ZSTD	CORR.				
56	49	13	1.1	0.38	0.48	-1.5	0.45	-1.6	0.54	0.46	61.5	51.1	056PM
66	49	13	1.1	0.38	0.34	-2.1	0.37	-2	0.84	0.46	76.9	51.1	066PM
17	48	13	0.95	0.37	0.68	-0.8	0.63	-0.9	0.55	0.46	53.8	51.2	017PM
28	48	13	0.95	0.37	0.8	-0.4	0.83	-0.3	-0.21	0.46	53.8	51.2	028PM
37	48	13	0.95	0.37	2.71	3.1	2.65	3	0.63	0.46	15.4	51.2	037PM
41	48	13	0.95	0.37	0.96	0	0.99	0.1	-0.44	0.46	38.5	51.2	041PM
45	48	13	0.95	0.37	0.86	-0.2	0.79	-0.4	0.84	0.46	53.8	51.2	045PM
47	48	13	0.95	0.37	1.35	0.9	1.23	0.7	0.64	0.46	61.5	51.2	047LM
61	48	13	0.95	0.37	2.49	2.8	2.39	2.7	0.64	0.46	15.4	51.2	061PM
76	48	13	0.95	0.37	1.06	0.3	0.91	-0.1	0.68	0.46	61.5	51.2	076PM
77	48	13	0.95	0.37	1.21	0.6	1.2	0.6	0.74	0.46	46.2	51.2	077PM
109	48	13	0.95	0.37	1.05	0.3	1.01	0.2	0.83	0.46	38.5	51.2	109PM
59	47	13	0.82	0.37	0.49	-1.5	0.46	-1.6	0.84	0.47	69.2	50.6	059PM
67	47	13	0.82	0.37	2.6	3	2.58	3	0.62	0.47	15.4	50.6	067PM
73	47	13	0.82	0.37	0.98	0.1	0.92	-0.1	0.01	0.47	46.2	50.6	073PM
93	47	13	0.82	0.37	2.14	2.3	1.88	1.9	0.44	0.47	38.5	50.6	093PM
98	47	13	0.82	0.37	0.59	-1.1	0.5	-1.4	0.6	0.47	69.2	50.6	098PM
7	46	13	0.69	0.36	0.31	-2.3	0.31	-2.4	0.58	0.48	76.9	50.3	007PM
9	46	13	0.69	0.36	0.66	-0.9	0.67	-0.8	0.39	0.48	46.2	50.3	009LM
11	46	13	0.69	0.36	0.61	-1	0.6	-1	0.54	0.48	61.5	50.3	011LM
12	46	13	0.69	0.36	0.33	-2.2	0.33	-2.2	0.55	0.48	76.9	50.3	012PM
79	46	13	0.69	0.36	0.69	-0.7	0.68	-0.8	0.32	0.48	69.2	50.3	079PM
97	46	13	0.69	0.36	1.82	1.8	1.79	1.8	0.79	0.48	30.8	50.3	097LM
103	46	13	0.69	0.36	0.64	-0.9	0.67	-0.8	0.84	0.48	61.5	50.3	103PM
104	46	13	0.69	0.36	3.76	4.4	3.84	4.5	0.35	0.48	0	50.3	104LM
24	45	13	0.56	0.36	0.43	-1.8	0.43	-1.7	0.41	0.48	61.5	48.9	024PM
82	45	13	0.56	0.36	0.61	-1	0.6	-1.1	0.61	0.48	61.5	48.9	082LM
92	45	13	0.56	0.36	0.69	-0.8	0.63	-0.9	0.62	0.48	46.2	48.9	092PM
30	44	13	0.43	0.35	0.26	-2.7	0.3	-2.4	0.62	0.49	92.3	47.6	030PM
42	44	13	0.43	0.35	0.79	-0.5	0.7	-0.7	0.77	0.49	53.8	47.6	042PM
87	44	13	0.43	0.35	1.01	0.2	1.1	0.4	0.52	0.49	30.8	47.6	087LM
18	43	13	0.31	0.35	0.58	-1.2	0.6	-1.1	0.54	0.49	61.5	46.2	018PM
84	43	13	0.31	0.35	1.86	1.9	1.81	1.8	0.53	0.49	30.8	46.2	084PM
31	42	13	0.19	0.34	0.44	-1.8	0.42	-1.8	0.66	0.5	61.5	45.9	031LM
35	42	13	0.19	0.34	1.54	1.4	1.48	1.2	0.84	0.5	38.5	45.9	035PM
38	42	13	0.19	0.34	1.37	1	1.34	0.9	0.75	0.5	23.1	45.9	038PM
81	42	13	0.19	0.34	2.02	2.2	1.92	2	0.27	0.5	23.1	45.9	081PM
78	41	13	0.08	0.34	0.94	0	0.91	-0.1	-0.19	0.5	61.5	44.5	078PM
100	41	13	0.08	0.34	0.58	-1.2	0.62	-1.1	0.59	0.5	53.8	44.5	100PM
10	40	13	-0.04	0.34	0.34	-2.3	0.33	-2.3	0.77	0.51	84.6	44.4	010PM
53	40	13	-0.04	0.34	0.65	-1	0.62	-1	0.6	0.51	46.2	44.4	053PM
60	40	13	-0.04	0.34	0.67	-0.9	0.71	-0.7	0.69	0.51	53.8	44.4	060PM
63	40	13	-0.04	0.34	0.53	-1.4	0.5	-1.5	0.7	0.51	61.5	44.4	063PM
21	39	13	-0.15	0.34	0.36	-2.3	0.37	-2.1	0	0.51	61.5	43.7	021LM
23	39	13	-0.15	0.34	0.36	-2.3	0.37	-2.1	0	0.51	61.5	43.7	023LM
25	39	13	-0.15	0.34	0.36	-2.3	0.37	-2.1	0	0.51	61.5	43.7	025PM
75	39	13	-0.15	0.34	0.36	-2.3	0.37	-2.1	0	0.51	61.5	43.7	075LM
29	38	13	-0.26	0.33	1.26	0.8	1.22	0.7	0.07	0.51	46.2	43.9	029LM
95	38	13	-0.26	0.33	0.77	-0.6	0.75	-0.6	0.15	0.51	53.8	43.9	095LM
32	37	13	-0.37	0.33	0.92	-0.1	0.96	0	-0.2	0.52	53.8	44	032LM
36	36	13	-0.48	0.33	0.97	0	0.95	0	0.63	0.52	53.8	43.7	036PM
15	35	13	-0.59	0.33	0.91	-0.1	0.91	-0.1	0.58	0.52	46.2	42.5	015LM
22	35	13	-0.59	0.33	0.37	-2.2	0.38	-2.2	0.81	0.52	61.5	42.5	022PM
64	35	13	-0.59	0.33	0.56	-1.4	0.56	-1.4	0.76	0.52	46.2	42.5	064PM
70	34	13	-0.7	0.33	1.86	2.1	1.91	2.1	0.1	0.52	30.8	42.6	070PM
46	28	13	-1.37	0.34	1.05	0.2	1.05	0.3	0.62	0.5	23.1	42.8	046PM
MEAN	48.8	13	1.26	0.42	1.03	-0.1	1.04	-0.1	53.7	51.8			
S.D.	7.3	0	1.29	0.21	0.67	1.6	0.7	1.6	18.7	7.2			

The data from "Table 7. Person Measure" reveals significant measurement values for several



entries, reflecting variations in individual performance. The entries with the highest total scores are numbers 5 and 68, both having a total score of 65 with a total count of 13 and a measure of 6.44, which reflects the maximum level of performance. Although they show maximum measures, these two entries also demonstrate extreme model fit results, with maximum MNSQ (Mean-Square) values and no variance in the data.

Conversely, entries with lower values, such as number 104 with a total score of 46 and a measure of 0.69, show greater variation in model fit results, with an MNSQ value of 3.76 indicating an outlier.

On the other hand, some entries display more balanced results with moderate measures and stable model fit. For instance, entry number 39 with a total score of 61 and a measure of 3.52 shows an infit MNSQ value of 1.03 and an outfit MNSQ value of 1.43, which are relatively close to the expected values, reflecting consistent performance. Moreover, entries with lower scores, such as numbers 27 and 66, both having a total score of 49 and a measure of 1.1, show infit and outfit MNSQ values close to the expected values, approximately 0.34 and 0.37 respectively, indicating better fit with the model.

Overall, this data illustrates variations in individual performance and the stability of model fit results, which are important in analyzing individual abilities within the context of this measurement.

Variable Map

The Rasch Model analysis in the table shows the distribution of items and respondents (persons) based on ability levels and item difficulty. In this table, the vertical axis represents the ability levels ranging from -2 to 5. In contrast, the horizontal axis separates items that are more frequently answered correctly (<frequ>) from those that are less frequently answered correctly (<rare>). The '+' lines at each ability level indicate the item difficulty level corresponding to the respondents' abilities. For example, at the ability level 0, there are several items grouped such as n1, n2, n3, n5, n7, n8, n9, n10, n11, and n12, meaning these items have a difficulty level balanced with the average ability of respondents at that level.

This distribution provides crucial insights into how well the items in the test match the respondents' abilities. For example, items at ability level 1 (n13) are easier for respondents with higher abilities to answer correctly, while items at ability levels 4 and 5 indicate that only respondents with very high abilities can answer them correctly. This suggests that the test has items that are sufficiently difficult to differentiate respondents with high abilities. Additionally, the even distribution of respondents across various ability levels shows that the test has a wide range of abilities and can effectively measure various levels of ability.

This information is very useful for developing and adjusting test items in the future to ensure better test validity and reliability. By understanding the distribution of items and respondents, test developers can identify which items need to be adjusted or improved to better balance item difficulty and respondent ability. This will help in creating a test that is fairer and more accurate in measuring individual abilities.

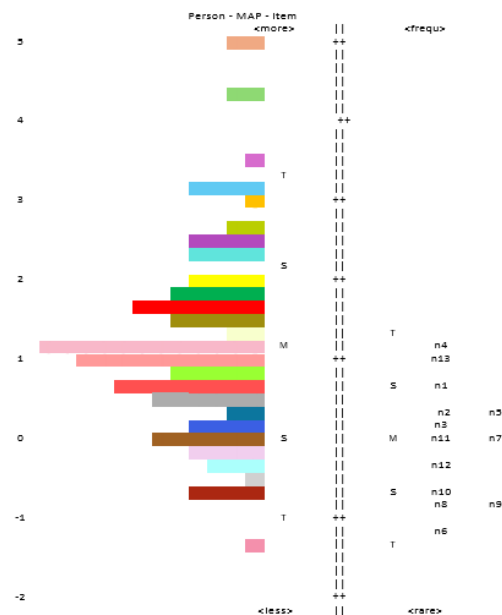


Figure 2. Map of Person and Item

CONCLUSIONS

The conclusion from this analysis indicates that AI has great potential to enhance effectiveness and efficiency in higher education. The Rasch Model results table illustrates how AI usage and effectiveness levels vary among individuals and items. The results show that most users fall within the middle to high frequency and effectiveness of AI usage, indicating a positive acceptance of this technology in the educational context.

AI plays a crucial role in supporting self-directed learning and self-assessment, which have been proven effective in increasing student independence and motivation. The data distribution in the table also suggests that items with different difficulty levels can be tackled with AI's assistance, demonstrating this technology's adaptability in meeting individual learning needs. Overall, the application of AI in higher education enhances the learning process and accommodates various levels of difficulty and student needs, making it a highly useful tool in the academic context.

In summary, AI's positive reception and effective use in higher education highlight its capacity to support diverse learning requirements and promote self-directed learning. By adapting to different difficulty levels, AI ensures that students at various ability levels can benefit from its implementation. This adaptability and support for autonomous learning make AI an invaluable asset in the academic field, contributing significantly to improving educational outcomes.

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