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Leveraging AI-Powered Adaptive Tutoring to Address Motivation Challenges in University Pedagogy

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Abstract. This study develops an intelligent tutoring system powered by ChatGPT and VARK framework to deliver personalized and adaptive learning experiences addressing low student motivation levels. The web-based prototype is tested on student samples at an Indonesian university using black box and usability analyses. Results indicate the system can enhance motivation by aligning teaching with individual learning styles and interests. The research contributes by demonstrating the potential of AI-based personalized education models to improve teaching quality and efficiency amidst prevailing pedagogical challenges. Practical insights are offered for institutes seeking technology-enabled solutions to re-engage students. Further testing on academic performance impact is warranted.

Keywords: Intelligent Tutoring System, VARK, Personalize Learning, Large Language Model

1. Introduction

In the industrial era 4.0, the Indonesian government strongly encourages the younger generation to get the highest education possible in order to prepare for a golden Indonesia. In the midst of these efforts, there are still a myriad of problems that must be resolved, one of which is low learning motivation. Based on the data obtained, Sebelas Maret University has a percentage of 45.18% of students categorized as low category learning motivation (Syahrozi et al., 2018) followed by Makassar State University with a percentage of 37.11% (Anas & Aryani, 2014). According to Ni Putu Krisna Maheni (2019), to increase learning motivation, learning style is the main key. Learning style is the way that students tend to choose in receiving and processing information or the way students prefer to receive learning.

Basically, every individual's learning style is different. Learning styles play a major role in determining how effectively students absorb information. Students who have a kinaesthetic learning style will have more difficulty absorbing information if the lecturer teaches using an auditory approach (Maheni, 2019).

In order to enhance students' learning motivation and optimize instructional activities within the classroom, it becomes imperative to overhaul existing educational systems and methodologies. In the context of Industry 4.0, the integration of Intelligent Tutoring Systems (ITS) with AI technologies such as the generative pre-trained Transformer (GPT) service presents an opportunity to facilitate personalized learning experiences for students. GPT, as a Large Language Model (LLM) within the realm of Natural Language Processing (NLP), possesses the capability to comprehend, manipulate, and interpret human language, thereby enabling the understanding of student characteristics and the creation of tailored learning environments. Personalized learning endeavours to accommodate individual student interests, where learners are categorized based on their preferred learning styles, namely visual, aural, read/write, and kinaesthetic (VARK). Such classification is deemed necessary as distinct learning modalities necessitate varied instructional approaches. Furthermore, ITS facilitates both formative and summative assessments to gauge students' comprehension levels during the learning process. Empirical evidence supports the efficacy of ITS in fostering adaptive learning, streamlining instructional procedures, and enhancing the efficiency and effectiveness of teaching and learning endeavours, as evidenced by a comprehensive review conducted by (Mousavinasab et al., 2021) encompassing 53 pertinent articles from diverse geographic locations. Previous scholarly efforts by (Troussas et al., 2019) and (Michalowski et al., 2021) have resulted in the development of ITS aimed at fostering adaptive learning environments. Nevertheless, extant systems exhibit limitations concerning the provision of personalized learning insights for individual students, a facet that could be enhanced through the utilization of LLM-based deep learning models.

This research aims to develop an Intelligent Tutoring System (ITS) capable of addressing the primary challenges in learning. The primary focus of the study is to design an ITS that can solve previously identified problems, with the hope of enhancing student motivation and creating an adaptive, optimal, and efficient learning environment. Additionally, this research has specific objectives, namely designing the architecture of the ITS according to students' learning styles, developing both frontend and backend designs for the ITS, and constructing an ITS system that integrates the VARK theory and generative pre-trained Transformer to achieve personalized learning. However, in conducting this research, there are several explicit limitations that need to be considered. Firstly, student classification is restricted to the four VARK learning styles without incorporating multi-modal learning styles. Secondly, student assessments remain homogeneous, lacking in-depth evaluation related to classification based on VARK learning styles. This study highlights the importance of integrating learning theory and technology in the development of an ITS that is responsive to the individual needs of students.

2. Literature Review

To conduct a research, it is very important to do a literature review. This is done to find out how the latest developments related to the object under study, theories that can be used, and what methods have been used by others related to the object of research. In addition, a literature review can make the writer/reader understand more about the object of research and as a foundation that strengthens the research to be carried out. In this chapter, the author will delve deeper into ITS, how to create ITS prototypes, and success stories of ITS implementation.

2.1. Personalize Learning

Every individual has different backgrounds, interests, goals, needs, so an effective learning experience must match the individual's characteristics and needs. In this approach, students are considered as constructors of their own knowledge, while learning is the process of knowledge construction. This approach aims to create a learning environment that is most suitable for the student to construct knowledge through meaningful experiences that are relevant to the learning material. Personalized learning has the following basic principles:

- Learner-centered: Understanding the learning style, knowledge level, needs, preferences, and strengths of each student in delivering the material.
- Flexibility and adaptability: Offering a wide variety of learning and teaching methods and resources for students to choose and access information according to their needs and desires.
- Intrinsic motivation: Creating meaningful and relevant learning experiences for students by connecting learning to their interests and goals.
- Continuous Progress Monitoring: Continuously collect student data for formative assessment to understand and respond to student progress.
- Creativity and Innovation: Encourage students' creativity in learning because each student is unique and has his/her own way to understand a material or knowledge.

In the personalized learning approach, technology can be a tool to help provide learning experiences that are tailored to individual needs. Technology can be used to collect data related to students, such as interests and learning progress, and used as a reference to provide learning experiences that suit individual needs and characteristics.

According to George and Lal (2019), personalized learning refers to the incorporation of a wide variety of student attributes including learning styles, knowledge levels, prior knowledge, and preferences as a reference in providing a learning platform.

In conclusion, personalized learning is a learning approach that emphasizes on individual experience and knowledge construction, by considering individual differences related to habits, motivation, and interests. This approach can provide relevant and meaningful learning experiences for each individual student (Shemshack & Spector, 2020).

2.2. Intelligent Tutoring System

According to Al-Bastami and Abu Naser (2017), ITS is a system deliberately designed to resemble a lecturer in teaching with the help of artificial intelligence technology. This system is able to assist students in learning a series of lessons, offer special instructions in learning using feedback, and know the way of learning desired by students. According to M.Adiwisastra and N.Basjaruddin (2017), ITS is a program equipped with artificial intelligence technology that functions as a forum for delivering information and evaluation media related to the learning process. In addition, the application is personalized to students by providing flexibility in applying their abilities/learning styles in receiving information, carrying out tasks, or training in lessons. Thus it can be concluded that ITS is a system supported by artificial intelligence to act like a lecturer in teaching students where the teaching approach is personalized based on student learning styles. The ITS system has an architecture, which is specifically designed to support learning activities. According to Nkambou et al. (2010), the ITS architecture consists of 4 parts:

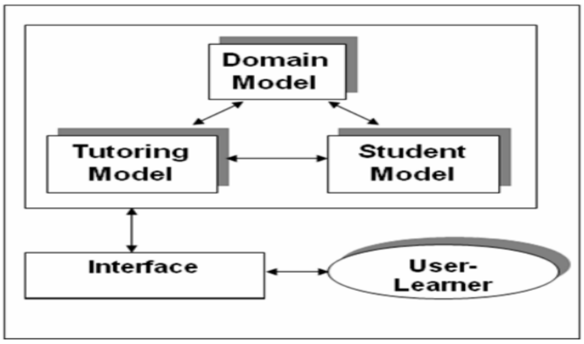

Fig. 1: The Four-Component Architecture

The domain model contains expert knowledge in the form of concepts and rules from a particular domain or it can also be called learning material related to the subject being taught. This model can be organized into curricula and use different structures such as hierarchies, semantic networks, frameworks, ontologies, and production rules. The model plays an important role as a rationale and presents appropriate explanations for students based on.

The student model is the core component of an ITS (Intelligent Tutoring System) and aims to contain as much information as possible about the student's cognitive and affective state and its development during the learning process. It has multiple responsibilities and roles, including gathering information, presenting student knowledge, making diagnoses, selecting optimal pedagogical strategies and evaluating students.

The tutoring model receives input from the student model and domain model to make decisions regarding strategies and actions required in the teaching process. The functions of this model include planning and delivering content and enabling interaction between students and teachers through a learning interface.

2.3. VARK Learning Theory

VARK builds on the pre-existing VAK (Visual, Aural, Kinesthetic) model. Flemming separated visual modality preference (V) with Read/Write (R), this is due to different tendencies. This is based on his research which concluded that students have different preferences for the written word and students who prefer symbolic information such as maps, diagrams, graphs. The VARK learning style was very popular in 1980 until now as a reference in learning for students or delivery methods by teachers / lecturers. According to Robertson et al. (Robertson et al., 2011), the four learning styles of students, namely visual, aural, read/write, kinesthetic, have their own characteristics that distinguish one from the other as depicted in table 1.

Table 1: Indicator Indices For Each Variable

Learning style:	Characteristics
Visual	Preference for using visual resources such as diagrams, pictures and videos. Like to see people in action.
Auditory	Need to talk about situations and ideas with a range of people; enjoy hearing stories from others.
Reader/writer	Prolific note-taker; textbooks are important; extensive use of journals to write down the facts and stories.
Kinaesthetic	Preference for hands on experience within a 'real' setting and for global learning.

In an effort to understand sensory modality preferences, Flemming conducted years of research using the VARK questionnaire. The results of his research are first, students have a preference for one modality or more than one modality (multi modal). Second, the preferred learning modality affects the individual's attitude including learning. Third, students' learning styles are not fixed, but stable in the short to medium term. Fourth, information accessed by methods that are aligned with students' modality preferences can make it easier for students to understand and motivate themselves in learning. Fifth, the match of learning styles and modality preferences can also increase perseverance in doing assignments, a deeper approach to learning, and produce active and effective learning. According to B. Widharyanto (Widharyanto, 2017), VARK is divided into 4 learning styles that include Visual (V), Aural (A), Read/Write (R), kinaesthetic (K) with the following explanation:

- Visual Learning Style: Students who have a visual learning style rely on the sense of eye or vision in the process of capturing information to understand the information. The learning preferences of students who have a visual learning style are easier to understand information that comes from pictures, designs, maps, diagrams, flow charts, graphs, hierarchies, photos, power points, movies, teacher demonstrations.
- Aural Learning Style: Students who have an aural learning style rely on their ear/hearing senses to capture and understand information. Students pay close attention to the teacher's pronunciation, intonation, and speaking speed when explaining, asking, and answering a question. The learning preferences of students who have an aural learning style are easier to understand information in the form of recordings, stories, presentations, and something that is read aloud.
- Reading/Writing Learning Style: Students who have a reading/writing learning style prefer to extract information through graphic text such as sentences, paragraphs, or discourse rather than pictures. Reading/writing learning style students find it easier to understand information through reading books (scientific, texts, lessons), magazines, newspapers, novels, letters, essays, brochures, summarizing, note-taking, and paraphrasing.
- Kinesthetic learning style: Students who have a kinesthetic learning style prefer to extract information through activities that involve physical or direct experience related to the material presented. Experience is very important for students who have a kinesthetic learning style. The learning preferences of students who have a kinesthetic learning style include making things, conducting experiments, playing drama, role playing, demonstrating something.

2.4. Large Language Model

One kind of machine learning algorithm called LLM is made to comprehend and produce text in human language. In order to understand the structure, grammar, and patterns found in a huge body of existing human language text, LLM analyzes the text. LLMs can be trained to perform a wide range of activities, including as question answering, text production, and translation. LLM understands and generates text using sophisticated deep learning neural network designs, like Transformer. The Transformer design is renowned for its capacity to generate reliable text representations and get around problems with lengthy text distances (Topsakal & Akinci, 2023).

Currently under development are a number of LLM models, one of which is GPT-4 (Generative Pre-trained Transformer 4), the most recent model in the GPT family. Compared to earlier iterations, this device can create text of a higher caliber and has a larger capacity. GPT-4 can carry out a variety of linguistic tasks with a high degree of artificial intelligence because it has been trained on larger data sets (OpenAI, 2023),(Eloundou et al., 2023).

Bidirectional Encoder Representations from Transformers, or BERT model, is one. Another well-liked LLM model is BERT. BERT's capacity to better comprehend context by comprehending words in their natural context is one of its key features. It has been widely applied to applications including sentiment analysis, information mining, and natural language understanding. Another model is the XLNet, which introduces a permutation-based training strategy to address some of the shortcomings of GPT. As a result, XLNet can comprehend increasingly intricate inter-word relationships (Yang et al., 2019).

2.5. Natural Language Processing

In learning how humans think (the real intelligence), the system must first understand human language using the concept of NLP. According to (Khurana et al., 2023) NLP is a branch of artificial intelligence and linguistics that focuses on making computers understand statements or words written in human language. NLP is divided into two parts namely NLU (Natural Language Understanding or Linguistics) and NLG (Natural Language Generation). NLU allows machines to understand and analyze natural language by extracting concepts, entities, emotions, keywords, etc. Linguistics is the science that deals with the meaning of language, language context and various forms of language. Whereas NGL is a process that generates meaningful phrases, sentences and paragraphs from internal representations. In the process there are three stages, namely identifying goals, planning how to achieve goals by assessing the situation and available communication resources, and writing the plan.

2.6. Chat-GPT

Chat GPT is a web-based application software that has the main function of answering all questions asked by users. GPT (Generative Pre-trained Transform) is a transformer architecture developed by the OpenAI company. Chat GPT is able to learn and understand patterns in human language and produce responses that humans can understand. The model is trained using massive data and combined with transfer learning techniques to produce better answer accuracy. Here are the advantages of GPT (OpenAI, 2023) :

- Chat GPT version 4 has an accuracy rate of up to 96% and is able to imitate humans in solving a problem.
- Chat GPT version 4 can use many languages in delivering its answers, including low-resource languages such as Latvian, Welsh, and Swahili. Unlike bard which is still limited to languages that can be used, namely English, Japanese and Korean.
- Chat GPT provides an open source API that can be used easily by developers in building applications.

2.7. Previous Research

Research conducted by M. Eryilmaz and A. Adabashi (2020), entitled "Development of an intelligent tutoring system using bayesian networks and fuzzy logic for a higher student academic performance" discusses the development of an intelligent tutoring system called the Bayesian Fuzzy Intelligent

Tutoring System (FB-ITS). The system uses artificial intelligence methods namely fuzzy logic and Bayesian networks to adaptively support students in the learning environment. The effectiveness of FB-ITS is evaluated by comparing it separately with two other Intelligent Tutoring System versions, namely Fuzzy ITS and Bayesian ITS. In addition, the FB-ITS system was also compared with existing traditional e-learning systems. To assess whether students' academic performance differs in different study groups, an analysis of covariance (ANCOVA) based on students' pre- and post-test scores was used. This study was conducted with a sample of 120 students. The results showed that students who studied with FB-ITS on average achieved significantly higher academic achievement than other students who studied with other systems. Regarding the time taken to complete the post-test, the results showed that students using FB-ITS took less time on average than students using traditional e-learning systems. From these results it can be concluded that the new system encourages speed in final exams and a high level of academic success.

Research conducted by E. Mousavinasab et al. (Mousavinasab et al., 2021), entitled "Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods" conducted a review of the Intelligent Tutoring System (ITS). This article focuses on the characteristics of ITS variants developed in various fields of education. The study was conducted from 2007 to 2017 from PubMed, ProQuest, Scopus, Google Scholar, Embase, Cochrane, and Web of Science databases. The study reviewed 53 articles grouped by inclusion criteria. The field of study in ITS is mostly computer science (37.73%). The most commonly used AI techniques in ITS are Rule-based reasoning based on operational conditions, data mining, and Bayesian networks with frequencies of 33.96%, 22.64% and 20.75% respectively. ITS technologies are effective for providing adaptive guidance and direction, assessing learners, determining and updating learning models, and categorizing learners. Most ITS are designed as web-based applications. Although these systems can facilitate the learning process, they are rarely used in decision making and problem solving.

Research conducted by W. Febriantoro and A. Nurhadi (2020), in their paper entitled "INTELLIGENT TUTORING SYSTEM DESIGN USING CHATBOT ON TRAINING MATTERS IN CONFIDENTIALS" discusses the design of a chatbot system using the Learn, Explore, Apply, and Evaluate (PEDATI) model using the Design science research (DSR) method which is commonly used in conducting information system implementation design research. The research was conducted to solve the problem of limited quota of face-to-face/offline training for civil servants (ASN). The results of the research conducted by them are that the prototype can follow the conversation flow that has been designed and can be utilized as a support for independent learning anywhere and anytime.

The study conducted by Michalowski et al. (2021) in their paper titled "Intelligent Tutoring System Design Using Chatbot on Training Matters in Confidentials" introduces a methodological framework with the aim of enhancing the development of customized courses tailored to augment patients' understanding of their medical conditions and prescribed treatments. Inspired by Intelligent Tutoring Systems (ITSs), the framework utilizes an eLearning ontology to articulate domain-specific knowledge and learner profiles, thereby facilitating the creation of personalized courses. By integrating the ontology with a procedural reasoning approach and precompiled plans, the authors operationalize a design methodology applicable across various disease states. The resulting courses, generated through their framework, are customized along four dimensions: the nature of the medical condition and corresponding treatment, the level of comprehension, preferred learning style based on the VARK model (Visual, Aural, Read/write, Kinesthetic), and proficiency in specific course content according to Bloom’s taxonomy. Tailoring educational materials based on these dimensions aims to engage and sustain patients' attention during their learning journey regarding their health conditions and treatment options. The proposed framework culminates in the development of personalized courses intended to equip patients with requisite knowledge for consultations with healthcare specialists and to foster an understanding of prescribed treatment regimens. The authors hypothesize that this enhancement in patients' comprehension of their healthcare will lead to improved outcomes. To validate the effectiveness of the framework, the authors demonstrate its applicability through two case studies: the management of anticoagulation treatment for a patient with atrial fibrillation and the management of lower back pain associated with lumbar degenerative disc conditions. The research employs predominantly qualitative methods, supplemented by a quantitative questionnaire, to assess the acceptability of the framework among the target patient population and medical professionals.

In their paper titled " Injecting intelligence into learning management systems: The case of adaptive grain-size instruction" (Troussas et al., 2019), introduce an innovative and intelligent Learning Management System specifically designed for instructing the Java programming language. Their system conducts diagnostic assessments of students' misconceptions by analyzing syntax errors and logical programming mistakes. Furthermore, it integrates students' learning styles, following the VARK model (Visual-Auditory-Read/Write-Kinesthetic Learner), to provide adaptive instruction tailored to individual preferences. The concept of "grain-size" instruction refers to the level of detail in domain knowledge imparted by a tutoring system to students. Thus, the adaptive delivery of domain knowledge aligns with students' knowledge levels and requirements. The efficacy of the proposed system was evaluated using a robust framework and the student's t-test, revealing a high level of acceptance for the presented model.

Based on previous research, it can be concluded that ITS can support personalized learning by providing a learning platform that suits the needs of students. ITS has also been proven to provide personalized, effective and efficient learning based on the review of 53 papers related to ITS development.

3. Methodology

The study was executed through a sequential progression comprising several distinct stages. Initially, data acquisition commenced with an exhaustive literature review, drawing from scholarly articles and pertinent books to fortify the research framework. Subsequently, the architectural blueprint of the envisioned system was meticulously crafted, delineating the operational schema and elucidating the interplay between various domains within the prospective prototype. Following this, a conceptual delineation was formulated, encapsulating a descriptive portrayal of the envisioned application. Subsequent to the conceptualization phase, system development ensued employing a prototype-centric methodology. The research methodology adopted was qualitative in nature, and the system underwent rigorous testing by stakeholders including students and faculty members affiliated with XYZ Private University.

3.1. Architecture Design

The following is a design of the ITS system architecture that will be built.

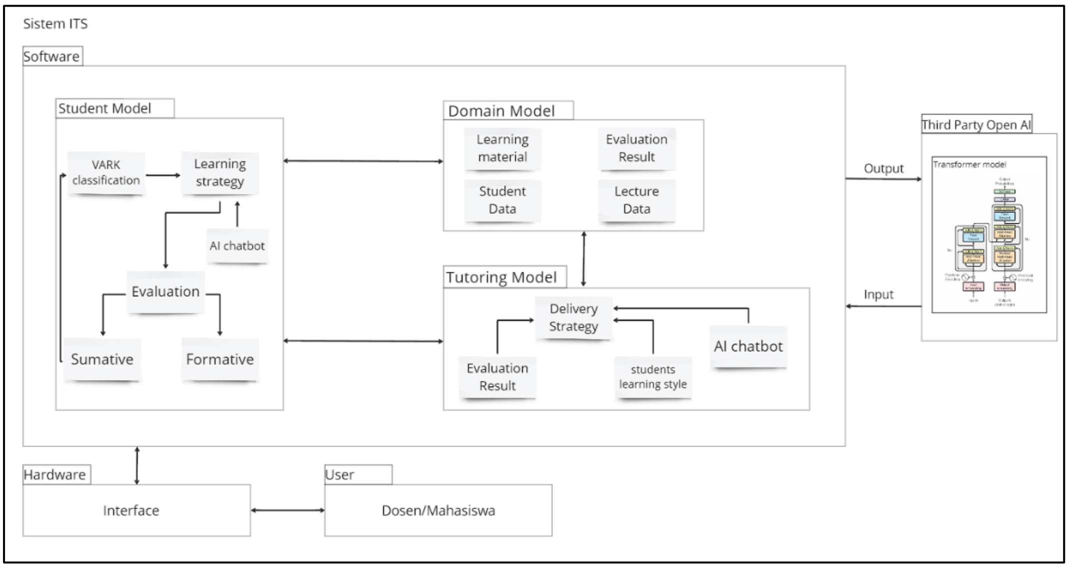

Fig. 2: ITS Architecture

Fig. 2 illustrates the interplay among three primary models within the Intelligent Tutoring System (ITS), each mutually reinforcing the others. The domain model serves as the repository and provider of learning materials, student data, and faculty information to facilitate the generation of personalized learning recommendations for both students and faculty members. The student model incorporates student profiles and learning materials from the domain model as additional parameters to deliver personalized learning experiences, while also facilitating the evaluation of student and faculty performance. The tutoring model operates to furnish personalized instruction and processes student learning outcomes as parameters to enhance the provision of personalized learning further. Moreover, the processed student evaluations can serve as foundational input for designing learning materials within the domain model.

The ITS under consideration leverages OpenAI's transformer model, which functions to receive queries from the ITS and provide outputs in the form of learning/teaching methodologies related to specific subjects and topics based on students' learning styles. In addition to GPT, another product with similar functionality is Bard by Google. However, for this study, the Chat GPT version 4 was utilized for several reasons as cited (OpenAI, 2023, p. 7):

- Chat GPT version 4 attains a precision level of up to 96% and exhibits human-like problem-solving capabilities.
- Chat GPT can operate across multiple languages, including those with limited resources such as Latvian, Welsh, and Swahili. In contrast, Bard is restricted to English, Japanese, and Korean.
- Chat GPT provides an open-source API, facilitating easy integration by developers in application development. Conversely, other products like Bard limit their API user base.

The ITS features a user interface serving as the intermediary platform displaying content and facilitating interaction between users and the system. This user interface is designed as a web-based application, ensuring accessibility anywhere and anytime as long as there is an internet connection.

The components depicted in Fig. 2, detailing the ITS system, are elaborated in table 2:

Tabel 2: Features of the ITS System

Component	Description	Source

VARK classification	Students are classified by learning style based on VARK theory. Classification is done by filling out the VARK pre-test.	(Widharyanto, 2017), (Sulistyanto et al., 2023)
Learning strategy	Students are equipped with learning strategies according to their learning style and the material being studied.	(Dutt et al., 2022)
AI chatbot	The AI chatbot is intended to explore the wider knowledge that is out there using the GPT 4 preview model.	(Topsakal & Akinci, 2023), (Febriantoro & Nurhadi, 2020)
Students Learning Style	The system visualizes the learning styles of students in the class as a reference in determining the delivery strategy.	(Widharyanto, 2017),(Sulistyanto et al., 2023)
Delivery Strategy	The delivery strategy feature serves to recommend the most appropriate teaching style for a particular class.	(Troussas et al., 2019), (Michalowski et al., 2021)
Learning Material	Learning materials serve as additional parameters for learning strategy and delivery strategy in generating recommendations. The materials that will be included in the ITS system in the prototype are Business mathematics, Advanced Topics In Management Information System, and Digital Business.	(Troussas et al., 2019), (Michalowski et al., 2021)
Student Data	Student data provider component as a basic reference to provide personalized learning.	(Michalowski et al., 2021)
Lecture Data	The component that provides data on lecturers responsible for a particular course.	(Michalowski et al., 2021)

3.2. Conceptual Design

The ITS application that was built consists of five use cases, consisting of two student use cases, two lecturer use cases and one use case that can be used by lecturers or students, the following is the proposed concept design:

- fill out the VARK questionnaire: Students who have just entered the website application for the first time in the semester can fill out the VARK questionnaire which amounts to five multiple choice questions where answer A represents visual learning style, B represents aural learning style, C represents read/write learning style and D represents Kinesthetic learning style. The results of student answers will be calculated by the system by summing up the points of each learning style chosen by the student. The highest point will be taken as the most effective way of learning for that student. The questionnaire is based on the VARK questioner created by (Limited, 2020).
- Looking at learning strategies (students): Students who have completed the VARK questionnaire this semester can view their learning styles and recommended study methods that suit them by visiting the "My Learning Style" page. The learning style recommendations will be personalized based on the course chosen by the student.

- Chat with AI chatbot (student/lecturer): Students/lecturers can chat with the chatbot to access more information or knowledge from outside by using the chatbot feature on the course details page.
- View the material delivery strategy (lecturer): Before starting learning in class, lecturers can view the delivery strategy for the course and session on the session details page. Delivery strategy recommendations are divided into 4 options: visual, aural, read/write, and kinesthetic.
- Seeing the learning style of students (lecturers): Before the lecturer starts learning in class, he can see the learning styles of students in the class by clicking the ITS submenu, then selecting the course, then clicking the people submenu on the session details page. The lecturer will be given information about the number of students to be taught, divided into 4 categories: visual, auditory, reading/writing, and kinesthetic columns.

3.3. System Development Life Cycle (SDLC)

In conducting system development, the System Development Life Cycle (SDLC) method used is the prototype method which has the following stages (Setiawan, 2021):

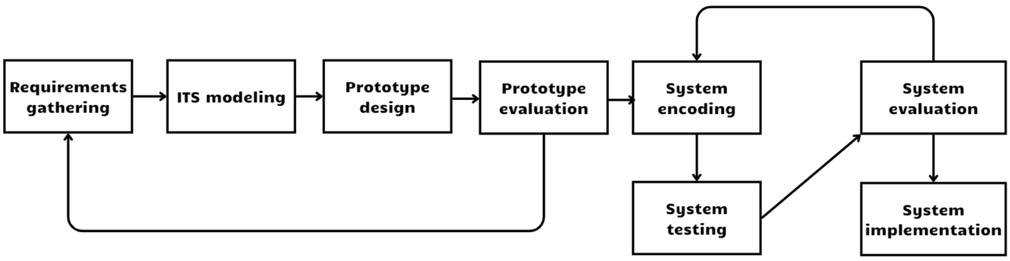

Fig. 3: SDLC Prototype

Description of the SDLC prototype model (Fig. 3):

- Requirements Gathering: identify all the requirements needed to build the system including hardware and software.
- ITS modeling: Implementing ITS modeling by integrating the elements of ITS architecture that have been available previously to provide personalized learning in the campus environment.
- Prototype Design: Create feature designs based on the ITS architecture as a blueprint. The design includes conceptual design, use case, activity diagram, system sequence diagram (SSD), and user interface (UI).
- Prototype Evaluation: Evaluate with users the design that has been made to find out whether the prototype model is in accordance with the needs of the university.
- Encoding System: The approved prototype model can be translated into a predetermined programming language.
- System Testing: The finished system will be tested using black box testing to find out if the system runs as it should. Black box testing is carried out by the study program and students totaling four testers.

- System Evaluation: Evaluation of the ITS system was carried out by running a usability test which was carried out twice. Usability tests are carried out by demoing ITS applications to users. The first usability test will be attended by 19 students and one lecturer. Then the second usability test will be conducted with a team of technology developers, curriculum developers, and IT teams from xyz universities. The evaluation includes all use cases contained in the ITS application which amount to five use cases. Evaluation is done to find out what should be improved and user responses to ITS. Aspects tested on the ITS system include intuitive

navigation (Triwicaksana S & Oktavia, 2023), response speed, interface and accuracy (Jáuregui-Velarde et al., 2023).
- Using The System: preparation of an ITS system implementation plan to the university's internal system.

SDLC prototype has the advantage that the system development time is relatively fast and prioritizes interaction with users so that system development can be in accordance with what is expected by users. SDLC prototype has the advantage that the system development time is relatively fast and prioritizes interaction with users so that system development can be in accordance with what is expected by users.

4. Result And Discussions

4.1. Implementation Result

The results of the implementation of the intelligent tutoring system have been successfully bolted using the local environment. The following is a display of the features in the ITS, on the VARK questionnaire page In Fig. 4, five multiple choice questions are presented. Students are asked to fill out the questionnaire according to their respective personalities then click submit to find out their learning style.

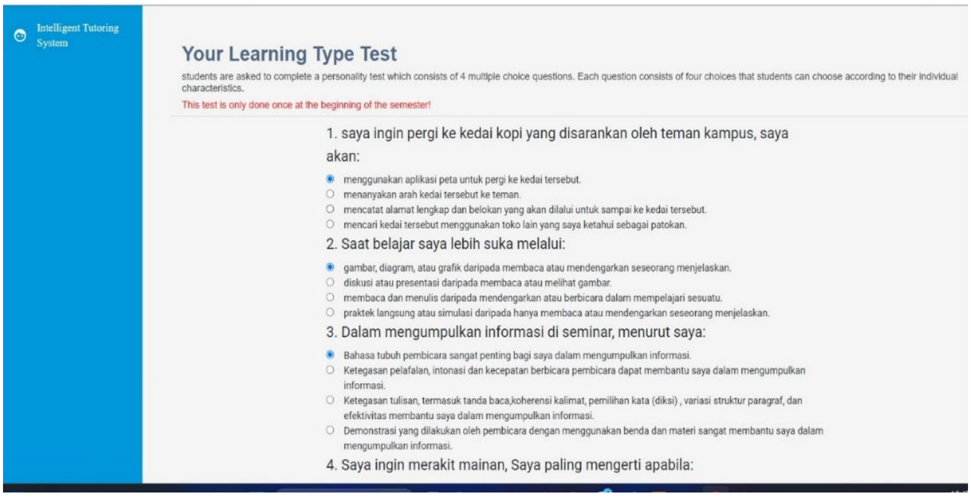

Fig. 4: VARK Questionnaire

Students who have filled out the VARK questionnaire can access the desired course page to be able to access materials, recommended learning strategies, and AI chatbot as illustrated in fig. 5.

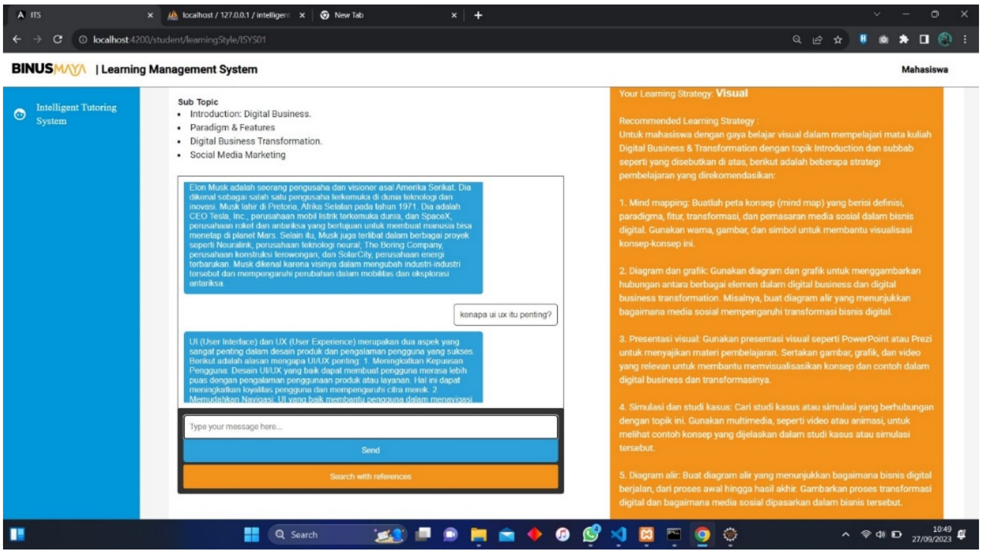

Fig. 5: Student's Course Page

In Fig. 5 there is an orange section that serves to accommodate learning styles in certain courses and sessions. On the left side there is a chatbot powered by GPT-4 so that the answers given will be more accurate and can be useful for increasing knowledge or solving problems faced by students. From the lecturer side, ITS has a feature to be able to see the course delivery strategy according to the needs of the class which is illustrated in fig. 6.

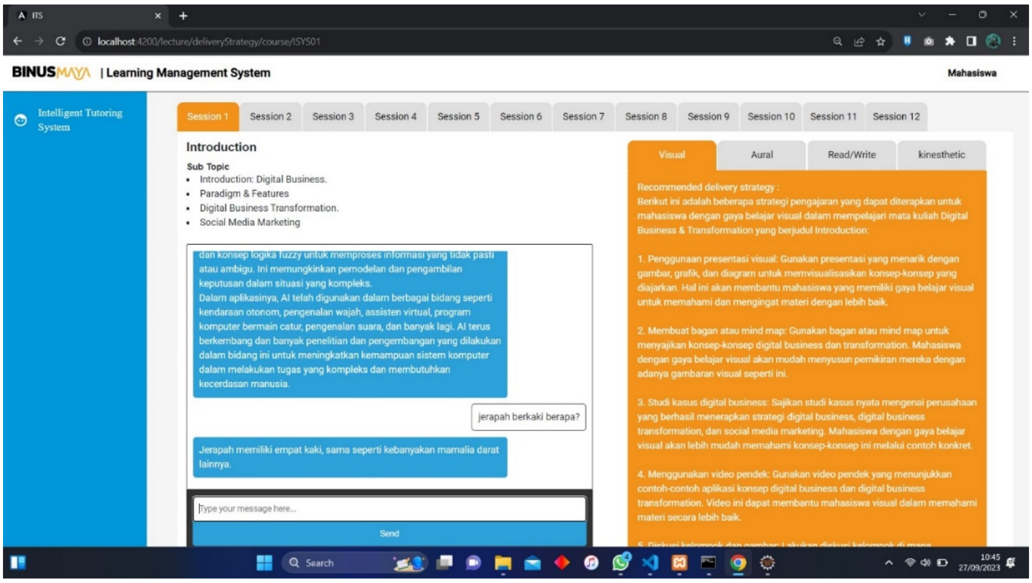

Fig. 6: Lecturer's Course Page

In Fig. 6 there is an orange-colored section that serves to accommodate delivery strategies in certain courses and sessions, lecturers can choose delivery strategies according to their needs. On the left side there is a chatbot powered by GPT-4 so that the answers given will be more accurate and can be useful for increasing knowledge or solving problems faced by lecturers.

In addition, the lecturer can see the learning style of the students in the class as illustrated in fig. 7.

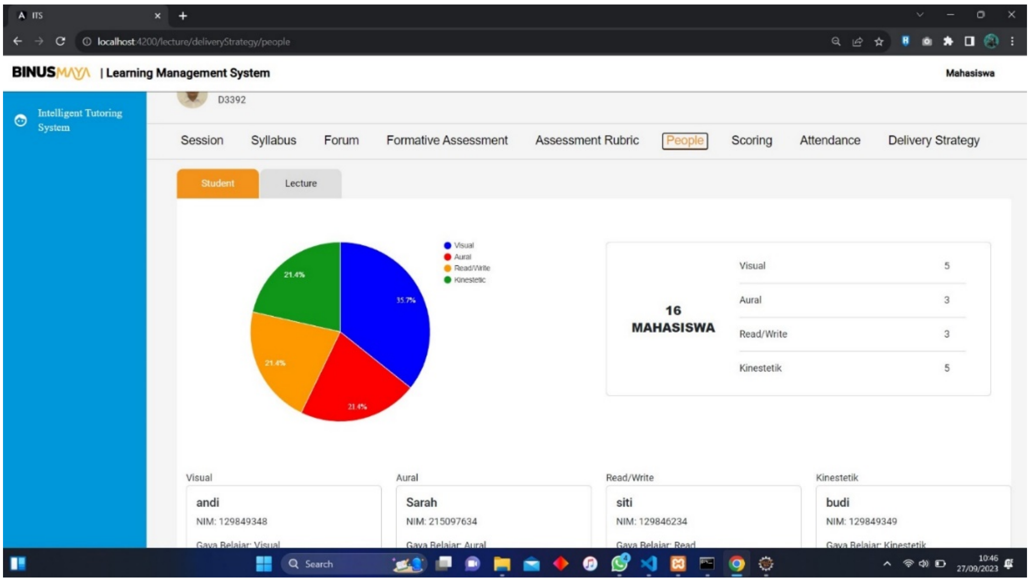

Fig. 7: People Page

In Fig. 7 there is data on students in the class along with learning styles in each individual which is divided into three kinds of visual displays, namely pie charts, learning style summaries on the right and division of students based on their respective learning styles.

4.2. Black Box Result

Blackbox testing is done to find out whether the features that are developed can run according to expectations. Table 3 is the result of the system trial.

Table 3. Blackbox Testing

ITS				
No	Scenario	Expected Result	Test Result	Status
1	Students fill out the VARK questionnaire to find out the most suitable learning style for themselves.	The system is able to determine student learning styles and update student learning styles in the database.	Success	Valid
2	Students see learning strategies on the course page	The system is able to generate learning strategies for students with certain learning styles, certain courses and certain sessions.	Success	Valid
3	Having a conversation with a chatbot hosted by Chat GPT 4	System and user can communicate with each other interactively.	Success	Valid
4	Lecturers view teaching strategies on the course page.	The system is able to generate a delivery strategy for that lecturer with a certain learning style, a certain course and a certain session.	Success	Valid
5	Lecturers see the learning styles of all students in the class.	The system is able to retrieve and display student data in the form	Success	Valid

		of graphs, learning style summaries, and student groupings based on learning styles.		

4.3. Usability Result

The usability test was conducted twice, first on October 10, 2023, attended by one lecturer and 19 MMSI Master Track students via Zoom video conference. The ITS usability test results show the enthusiasm of students and lecturers regarding the application of personalized learning powered by AI can help them in getting a better learning experience and broader knowledge. However, the ITS System still has obstacles that have an impact on the users' experience in using the application, namely the time it takes ITS to generate answers is quite long, namely 1-2 minutes to display answers to the features View learning strategies, View material delivery strategies, AI Chatbot, Formative Assessment support, and student exam scoring using AI. In addition, learning strategies and material delivery that are still less specific to student learning styles are a concern in the development of the ITS system. Table 4 contains the results of the first usability test.

Table 4. Blackbox Testing

No	Test Aspect	Description	Result
1	Response speed	The time taken by the system to generate answers from GPT-4 regarding all features of the ITS.	Very long, the time taken to generate an answer from GPT-4 ranges from 1-2 minutes depending on the length of the answer.
2	Intuitive navigation	How easily users understand how to operate the ITS to achieve their goals.	The system is very easy to use. Because ITS is designed according to the xyz website that is commonly used by students / lecturers.
3	Interface	Assessment of interface design, layout, and graphical elements to ensure a good overall visual experience.	Highly commendable, as the design format aligns perfectly with the XYZ website.
4	Accuracy	Referring to the accuracy of the Intelligent Tutoring System (ITS) in providing responses aligned with user requests and needs.	"Moderately accurate, while the system is capable of generating learning and teaching recommendations, it still lacks specificity regarding student learning styles.
5	Response speed	The time required by the system to generate responses	Extremely lengthy; the time required to

		from GPT-4 related to all features of the ITS.	generate responses from GPT-4 ranges between 1-2 minutes, depending on the length of the response.

After the code improvements were made in the ITS system based on the results of the initial usability test, a second usability test was conducted on November 23, 2023, through a hybrid approach, with offline testing held in the Digital Team's room and online testing via Zoom. This session was attended by the XYZ university technology development team, IT Team, and curriculum developers. The results of the usability test received positive feedback from the Digital and IT teams. They expressed the opinion that the ITS system has great potential to be implemented at the university. They noted that the system aligns well with current technological advancements and has the potential to enhance the efficiency and effectiveness of teaching and learning activities at XYZ University. In terms of utility, the ITS system could serve as an initial step towards realizing XYZ University's long-standing goal of personalized learning. Table 5 presents the results of the second usability test.

Table 5. Usability Testing Result

No	Test Aspect	Description	Result
1	Response speed	The time taken by the system to generate answers from GPT-4 regarding all features of the ITS.	Near Real Time
2	Intuitive navigation	How easily users understand how to operate the ITS to achieve their goals.	Very easy
3	Interface	Assessment of interface design, layout, and graphical elements to ensure a good overall visual experience.	Very good
4	Accuracy	Referring to the accuracy of the Intelligent Tutoring System (ITS) in providing responses aligned with user requests and needs.	Good because there are no complaints about the results generated by AI both in terms of speed, accuracy and flexibility of answers based on user needs.
5	Response speed	The time required by the system to generate responses from GPT-4 related to all features of the ITS.	The use of ITS is very easy to understand because each page has instructions on how to use ITS.

4.4. Discussion

The findings from the blackbox and usability testing provide valuable insights into the effectiveness of the developed ITS in achieving the overarching research objective of enhancing student motivation through an adaptive learning environment. The successful functionality of the ITS across various use cases, as demonstrated in the blackbox testing, underscores its capability to deliver reliable and consistent performance, thereby fostering a conducive learning experience. Additionally, the positive user feedback obtained from the usability testing, particularly regarding the system's speed of answer generation, ease of navigation, interface display, responsiveness, and comprehension, indicates that the ITS effectively caters to the diverse needs and preferences of students. By adapting to individual learning styles and preferences, the ITS creates a personalized learning environment that is engaging and tailored to each student's unique requirements, thereby promoting intrinsic motivation and active participation in the learning process. Consequently, these findings contribute significantly to the advancement of educational practices by highlighting the potential of adaptive ITS in cultivating student motivation and enhancing learning outcomes. Moreover, the interpretation of these findings underscores the importance of incorporating adaptivity and personalization into educational technologies to better address the motivational needs of students and optimize their learning experiences.

5. Conclusion

The prototype intelligent tutoring system effectively showcases the utilization of AI-driven adaptive learning techniques to deliver tailored educational experiences aimed at addressing motivational deficits. ITS effectively caters to the diverse needs and preferences of students. By adapting to individual learning styles and preferences, the ITS creates a personalized learning environment that is engaging and tailored to each student's unique requirements, thereby promoting intrinsic motivation and active participation in the learning process. Nonetheless, a broader evaluation encompassing a larger cohort of students and diverse courses is imperative to substantiate its efficacy. Examination of the findings reveals promising potential for personalized systems to redefine the pedagogical landscape. Nevertheless, practical challenges persist, particularly concerning content suitability and ethical considerations. On the system development front, the incorporation of a chatbot feature devoid of direct answer provisions but instead offering hints for student learning could foster deeper comprehension and encourage critical thinking.

References

Adiwisastra, M. F., & Basjaruddin, N. C. (2017). Intelligent Tutoring System Untuk Mengukur Kemampuan Kognitif Dalam Fisika Dasar Berbasis Metode Bayesian Network. IJCIT (Indonesian Journal on Computer and Information Technology), 2(2), 40–47.

Al-Bastami, B. G. H., & Abu Naser, S. S. (2017). Design and Development of an Intelligent Tutoring System for C# Language. European Academic Research, IV(10), 8796–8797. www.euacademic.org

Anas, M., & Aryani, F. (2014). Motivasi Belajar Mahasiswa. Jurnal Penelitian Pendidikan INSANI, 16(1), 41–46. https://hariansinggalang.co.id/motivasi-belajar-mahasiswa-merosot/

Dutt, S., Ahuja, N. J., & Kumar, M. (2022). An intelligent tutoring system architecture based on fuzzy neural network (FNN) for special education of learning disabled learners. Education and Information Technologies, 27(2), 2613–2633. https://doi.org/10.1007/s10639-021-10713-x

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. http://arxiv.org/abs/2303.10130

Eryilmaz, M., & Adabashi, A. (2020). Development of an intelligent tutoring system using bayesian networks and fuzzy logic for a higher student academic performance. Applied Sciences (Switzerland), 10(19). https://doi.org/10.3390/APP10196638

Febriantoro, W., & Nurhadi, A. (2020). Perancangan Intelligent Tutoring System Menggunakan Chatbot pada Mata Pelatihan Barang Dalam Keadaan Terbungkus. PANCANAKA Jurnal

Kependudukan, Keluarga, Dan Sumber Daya Manusia, 1(1), 10–20. https://doi.org/10.37269/pancanaka.v1i1.33

George, G., & Lal, A. M. (2019). Review of ontology-based recommender systems in e-learning. Computers and Education, 142(July), 103642. https://doi.org/10.1016/j.compedu.2019.103642

Khurana, D., Koli, A., Khatter, K., & Singh, S. (2023). Natural language processing: state of the art, current trends and challenges. Multimedia Tools and Applications, 82(3), 3713–3744. https://doi.org/10.1007/s11042-022-13428-4

Limited, V. (2020). Kuesioner VARK (Version 8.01). 7–9.

Maheni, N. P. K. (2019). Pengaruh Gaya Belajar Dan Lingkungan Teman Sebaya Terhadap Hasil Belajar Mahasiswa Di Jurusan Pendidikan Ekonomi Universitas Pendidikan Ganesha. Jurnal Pendidikan Ekonomi Undiksha, 11(1), 85. https://doi.org/10.23887/jjpe.v11i1.20077

Michalowski, M., Wilk, S., Michalowski, W., O'sullivan, D., Bonaccio, S., Parimbelli, E., Carrier, M., Le Gal, G., Kingwell, S., & Peleg, M. (2021). A health elearning ontology and procedural reasoning approach for developing personalized courses to teach patients about their medical condition and treatment. International Journal of Environmental Research and Public Health, 18(14), 1–28. https://doi.org/10.3390/ijerph18147355

Mousavinasab, E., Zarifsanaiey, N., R. Niakan Kalhori, S., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods. Interactive Learning Environments, 29(1), 142–163. https://doi.org/10.1080/10494820.2018.1558257

NKambou, R., Bourdeau, J., & Mizoguchi, R. (2010). Advances in intelligent tutoring systems ; Studies in Computational Intelligence. In Advances in intelligent tutoring systems ; Studies in Computational Intelligence.

OpenAI. (2023). GPT-4 Technical Report. 4, 1–100. http://arxiv.org/abs/2303.08774

Robertson, L., Smellie, T., Wilson, P., & Cox, L. (2011). Learning styles and fieldwork education: students' perspectives. New Zealand Journal of Occupational Therapy, 58(March 2011), 36+. http://go.galegroup.com/ps/i.do?id=GALE%7CA263992729&v=2.1&u=tel_a_tbr&it=r&p=AONE&sw=w LA - English

Setiawan, R. (2021). Metode SDLC Dalam Pengembangan Software - Dicoding Blog. https://www.dicoding.com/blog/metode-sdlc/

Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. Smart Learning Environments, 7(1). https://doi.org/10.1186/s40561-020-00140-9

Sulistyanto, H., Prayitno, H. J., Sutama, Narimo, S., & Sutopo, A. (2023). The Effectiveness of Hybrid Learning-Based Adaptive Media to Empower Student's Critical Thinking Skills: Is It Really for VARK Learning Style? Asian Journal of University Education, 19(1), 95–107. https://doi.org/10.24191/ajue.v19i1.21219

Syahrozi, H., Rochsantiningsih, D., & Handayani, E. I. P. (2018). IMPROVING STUDENTS' MOTIVATION IN LEARNING ENGLISH USING MOVIE CLIP. 1991.

Topsakal, O., & Akinci, T. C. (2023). Creating Large Language Model Applications Utilizing LangChain: A Primer on Developing LLM Apps Fast. International Conference on Applied Engineering and Natural Sciences, 1(1), 1050–1056. https://doi.org/10.59287/icaens.1127

Troussas, C., Krouska, A., & Virvou, M. (2019). Injecting intelligence into learning management systems: The case of adaptive grain-size instruction. 10th International Conference on Information, Intelligence, Systems and Applications, IISA 2019, 1–6. https://doi.org/10.1109/IISA.2019.8900779

Widharyanto, B. (2017). Gaya Belajar Model Vark Dan Implementasinya Di Dalam Pembelajaran Keterampilan Berbahasa Indonesia. 1st International Conference on Education, Language, and Arts, July, 1–16. https://www.researchgate.net/publication/327869001

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R., & Le, Q. V. (2019). XLNet: Generalized autoregressive pretraining for language understanding. Advances in Neural Information Processing Systems, 32(NeurIPS), 1–18.