Technology Adoption and Peer Influence on Student AI Research Tools Purchase Intention

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Abstract

Technological advancement has brought changes into how researchers conduct their research, Artificial Intelligence (AI) is one of the most impactful technologies that change the process. Through the lens of Technology Adoption Model (TAM) Framework, this research is aimed to uncover the relationship between technology adoption factors and peer influence in students' intention toward buying AI research tools. Previous research is still limited toward explaining technology adoption toward students' purchase intention and neglected social factors such as peer influence, therefore reinforcing the importance of the research. The study will be conducted on 100 State University of Jakarta students and Analysis of the data will use Partial Least Square (PLS) Structural Equation Model to explain the connection between variables.

Keyword: Tech Adoption; Purchase Intention; Peer Influence; Student; TAM

1. Introduction

Technology is one of the foundations of human life. Starting from the creation of light bulbs, telephones, to steam engines, the development of technology in human civilization has brought significant changes to the way they live their lives. Technology disruption has a positive impact on the business world, ranging from operational efficiency, opening new business opportunities, to developing new skills needed to understand the technology. In the COVID-19 era, there has been a rapid acceleration in the adoption of digital technology around the world, including in Indonesia. By 2021, Indonesia will have 202 million internet users contributing $70 billion to the digital economy, with projections to reach $146 billion by 2025 (World Economic Forum, 2022). With this projected increase in internet users, digital technology innovations are becoming more accessible to the wider community, accelerating penetration into various sectors, including education and research. One of the most prominent technological innovations in recent years is Artificial Intelligence (AI), which enables machines to perform tasks that would normally require human intelligence, such as learning, problem-solving, and data analysis (Göde, 2023). One of the latest breakthroughs in the development of artificial intelligence is Generative AI or GenAI, an AI system that is capable of understanding human language and generating new content accordingly.

One important area where GenAI has made a significant impact is in the field of academic writing and research methodology. GenAI has been incorporated into innovative products to aid research, such as ConnectedPaper that provides visualization services of journal relationships, Scite that enables researchers to conduct research reviews, and other GenAI products that have been specialized for research purposes. In higher education, AI is increasingly being adopted as a tool for research. Based on a survey from Tirto.id (2024), 56% of students in Indonesia reported having used AI in the completion of their academic assignments. Apart from assignments, AI is also increasingly used to support the academic research process. A survey from Noorden and Perkel (2023) showed that 57% of students in the US use AI in their research, and 92% stated that AI helps speed up the research preparation process. Various studies have shown that AI tools can help researchers ideate, organize, and refine their work. For example, Korinek discusses how large language models (LLMs) can help economists by providing feedback, conducting background research, and even performing data analysis and coding tasks, thus increasing productivity and creativity in research efforts (Korinek, 2023). Similarly, Conde emphasized the implications of AI tools in academic writing, noting its ability to summarize, translate, and generate relevant citations, which can significantly assist researchers in producing high-quality academic output (Conde, 2024).The acceptance process of these AI-based research tools is influenced by several factors, one of which is the level of public adoption in using this new technology.

In the context of this study, the use of AI for research continues to grow, with the emergence of various AI-based products such as Scite, Scihub, ResearchRabbit, and ConnectedPapers. Most students who use these products tend to take advantage of the free features provided. However, previous research indicates that the usability value of AI products encourages users to invest in premium services (Fu et al., 2023). Similar trends have

been investigated in several other sectors, such as the banking industry (Lazo, 2023; Ghandour, 2021), healthcare (Lee, 2023; Pillai & Sivathanu, 2020), and supply chain (Al-Shami et al., 2021).

These studies generally focus on industries outside of education. However, research on the trend of Indonesian students' willingness or intention to purchase premium AI services for research is still minimal. With the increasing use of AI by students in Indonesia (Siahaan, 2024), it is important to understand whether technology acceptance factors such as perceived ease of use and perceived usefulness drive students' intention to invest in AI-based research assistant services. In addition, external factors such as the influence of students' peers may influence their perceptions and decisions to purchase AI products for research purposes. To answer this question, the researcher proposed a study entitled "The Effect of Technology Adoption, Institutional Support, and Peer Influence toward Student Purchase Intention on AI Research Tools".

2. Literature Review

2.1 Technology Acceptance Model

The Technology Acceptance Model (TAM) was introduced by Davis in 1989 with the aim of broadening the understanding of the factors behind technology obligation user. The model addresses two prime concepts: perceived usefulness and ease of use. When an individual considers that, with the help of the technology in question, he/she will be more efficient, then that technology is consider to be useful. Regarding perceived ease of use, it's the ease with which a person believes he or she can use the technology without undue effort (Brasier & Wan, 2010; Ma & Liu, 2004; Wahyudi, 2023). The model has probably become the most dominant model in the area of technology acceptance due to its straightforwardness and the capacity to account for a variety of user behaviors across different settings (Perwira, 2023; Teo & Jarupunphol, 2015).

The first assumption under TAM is that user behavior towards technology can be affected by two major determinants, these are: Perceived Ease of Use and Perceived Usefulness . It interprets in such a way that adoption will be likely among users of the technology if it is perceived to be simple and beneficial (Oktaria, 2024; Colvin & Goh, 2005). Moreover, TAM goes further to postulate that factors like user attitudes towards technology will also determine the intention to use ("Attitude Toward Using"), and consequently, their actual use of that technology ("Behavioral Intention to Use") (Chan & Teo, 2007; Al-Mamary & Shamsuddin, 2015).

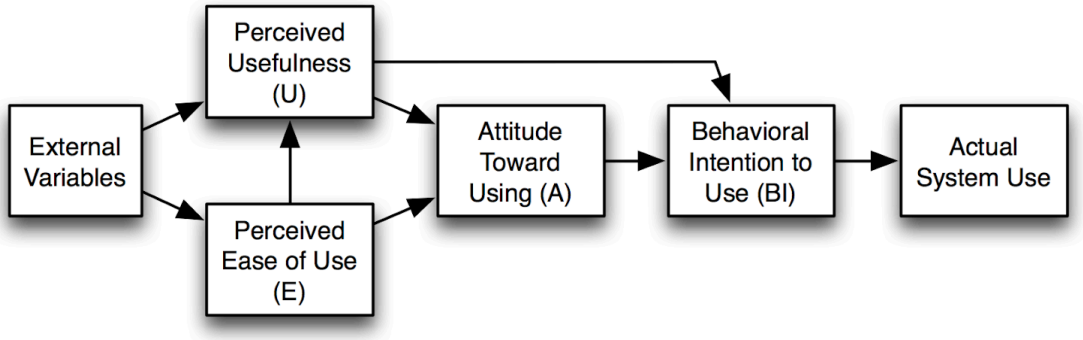


Figure 2.1 Technology Acceptance Model (TAM)

The reason for choosing the TAM as a starting point of research is the strength of this model in clarifying the puzzle regarding the consumer behavior in regard to the implementation of the technology acceptance. The utilization of TAM is also not restricted to just the application of technology but rather how the key components of TAM could contextualize other factors in business education and health (Wang et al., 2022; Venkatesh & Davis, 2000, Bouwhuis et al., 2008). Employing TAM to explain consumer purchase behavour in relation to new technology brings into picture the highlighting of factors influencing user attitudes and intentions. Various studies with the use of TAM typically include measuring PU and PEOU as well as their relations with other variables like subjective norms motivation (Brasier & Wan, 2010; Ma & Liu, 2004; Al-Maroof et al., 2021). So the development of technology acceptance model not only helps explain how users perceive and use technology, it also helps technology developers to produce more appropriate and expectable products for the users (Perwira, 2023, Hong et al 2021, Simsek and Ates 2022).

2.1.1 Perceived Ease of Use

PEOU is defined as the level of user's belief that they would not put in any effort in utilizing the specific system. It is asserted that if users see technology as easy to use, they are more willing to embrace the technology because the perception of such technology decreases the barriers needed to learn and use new systems (Sidanti et al., 2021; Paper & Fayad, 2015; Gefen & Straub, 2000). The institutional model of technology acceptance postulates that PEOU has a direct effect on PU and consequently the users' attitudes and their intention to utilize the technology (Cross-country analysis, 2011; Setiawati et al., 2019).

Users believe that the ease of use of the software is quite high due to several factors. These include, the design of the interface, the support and training available to the user and the technology itself (Genoveva et al., 2023; Arief, 2023; Nurhayati et al., 2022). A system with PEOU and easy to comprehend systems as few barriers as impenetrability to the user's comprehension, directly achieves its aim. Also, effective training and support can also instill confidence in the users to use the technology more often, and therefore, their rate of adoption will tend to rise (Mustapha & Obid,

2015; Lee et al., 2005). In addition, technology being appropriate to what skills and experience the user already has may also raise perceptions of ease of use, especially for the older generation groups that had been accustomed to other sets of technology (Genoveva et al., 2023; Hermawan et al., 2022).

PEOU seems to be very relevant in the digital age, especially in relation to the use of Artificial Intelligence (AI) technologies. The conviction that AI systems require little effort to use and adapt personal systems to them encourages the adoption of AI technologies. For instance, users' acceptance of mobile payment technologies and electronic patient portals is greatly affected by the perception of ease of use (Honein-AbouHaidar et al., 2020; Setiawan & Setyawati, 2020). Since AI systems are based on many algorithms and data analysis, its perception as user-friendly helps in raising the acceptance of such technologies across the spectrum of users (Nofirda & Ikram, 2023).

2.1.2 Perceived Usefulness

According to the Technology Acceptance Model, 'perceived usefulness (PU)' is a central concept that explains individual usage realization, while in regard to a specific technology, it states that the greater the belief by a user on the technology enabling them to perform their job better, the higher their intention to employ the said technology. For example, in the context of this theory, PEOU and PU are recognized as the two important factors behind the acceptance of technology (Ozturk, 2016; Askari et al, 2020). It has been established in relevant literature that many users are more likely to adopt new technologies including mobile apps and AI systems if they perceive them to be useful (Dou et al, 2017; Jeong & Yoon, 2013).

Numerous factors point out that users have a strong level of perceived usefulness. These include the ability of the technology to address specific needs, improve efficiency, and access dependable and credible information (Li, 2024; Baizal et al, 2016). Furthermore, the enjoyable aspect of using the technology as well as the level of trust that users have towards the technology can strongly increase perceived usefulness (Yan & Wang, 2012; Almarashdeh et al, 2011). To illustrate, in the case of mobile banking, it was reported that perceived usefulness was influenced by perceived trustworthiness and overall satisfaction which in return increases the likelihood of using such services (Jeong & Yoon, 2013). In addition, the role of AI in educational environments has indicated that perceived usefulness is a key factor in teachers' intentions to use AI assessment systems stressing that clear advantages are crucial for acceptance (Mafi, 2023).

One of the more prominent behavioral models is the relation between perceived usefulness and usage of technologies for instance artificial intelligence (AI). AI technologies are more likely to be embraced by users if they justify their usefulness in the tasks or daily activities'. For example, research has had it that AI applications which eliminate bottlenecks to adoption of technology are likely to have higher acceptance rates across the board including low literacy or cognitive impaired users (Hasan et al., 2021). In addition, AI technologies are commonly recognized to be useful because they save time and increase accuracy of performance in many

fields, including the provision of primary health care and customer support (Na et al., 2023; Mafi, 2023).

2.1.3. Attitude toward Using

Attitude toward Using is a vital construct as it depicts how an individual evaluated even the choice of technology in a positive or negative manner. It is postulated that this attitude has great impact on behavioral intentions to use the technology, which in turn determines the usage behavior of the technology. Very specifically, TAM proposes that the perceived usefulness and the perceived ease of use are the key factors which determine the attitude towards using technology which in turn, determines the intention to use the technology (Venkatesh, 2000; Setyawati & Polar, 2022).

Attitude toward using is a user's affective predisposition to accept a technology, including perception and beliefs on the technology's usefulness and usability. This construct is crucial in user adoption as it acts as a moderator to the association of external variables (e.g. social influence and facilitating conditions) and behavioral intention. For example, it has been established that positive attitude motivates users to adopt novel technologies while negative attitude promotes resistance and reduced use of such technologies. More, for instance, has indicated that negative attitude through organizational complex resistance contributed to adoption failure. So, for instance, acceptable attitude for exercising force is needed to use technology.

Undoubtedly attitude toward using influences particular features of a product when making purchasing decisions. A favorable attitude is capable of raising intention to purchase as users are willing to invest more on the features they deem useful and easy to work with (Alhogail, 2018; Zhong-qing et al., 2019). A case in point is that there are studies which show that the perceived usefulness and ease of use actually act as significant moderators of the relationship between attitude and purchasing intention in a range of situations, such as mobile financial services and payments with e-wallet applications (Himel et al., 2021; Zhong-qing et al., 2019). And again, when users' behavior is directed by a positive attitude towards technology, they tend to search for and use more features and functions, thus increasing their active use and satisfaction of the product (Karaca, 2022; Mansour et al., 2016). This highlights the need to be purposeful in nurturing a favorable attitude towards the users as one of the ways of increasing technology acceptance and feature integration.

2.2 Peer Influence

Peer influence at commerce and business studies includes the effect of people within a social setting on one another's attitudes, actions, and the purchasing options of each individual. That influence can take different forms, including: peer advice, activities on social media, or the consumption of products by a group of people. This is most relevant when considering e commerce as well as social commerce, where consumers look to their friends' actions for guidance on what products to purchase. Research has revealed that good

recommendations from peers make a consumer more likely to buy a product, but a negative review can result in the opposite outcome (Ngo, 2023; Mapanje, 2024).

Peer influence on the perception of the customer in regard to adoption of a certain product has an impact that is beyond description. Precisely, when potential customers see certain peers of theirs advertising or using some or other product, it instills some level of trust on the product in question. This is particularly in regard to online platforms where other people's comments or pictures of them enjoying the product are crucial inputs in the mind of the consumer (Ngo, 2023; Mapanje, 2024). In addition, the emotional aspect brought about by cheerful peers adds up to the esteem and loyalty a consumer has for a certain brand which in turn leads to purchasing intention (Kim et al., 2009).

The peers have great effect on the consumer behavior as far as purchasing of particular products and services is concerned as well. Peer pressure is argued to stimulate purchases which are not planned as one may need to take the opinions which are preferred by the members of his or her social group (Lee & Kacen, 2008; Yan, 2023). Furthermore, social media platforms have emerged to be important peer influence factors where consumers look for recommendations and endorsements from their friends and influencers, thus modifying their purchasing patterns (Mapanje, 2024; Alotaibi & Aloud, 2023). This tendency has been found to be more intense among the young peoples as they tend to have more interactions and also aspire to be accepted by their peers (Gil et al., 2017; Yan, 2023).

To define and measure peer pressure, scientists adopt methods such as mapping the number of peer contacts, the credibility of peer recommendations, or the emotional response when a peer is praised. Moreover, they can also use surveys to gauge the power of peer opinions on the consumer's turn of mind and behavior and compute the quantum of peer pressure exerted in decision making (Yusoff et al., 2021; Chen et al., 2020). Furthermore, the metrics of social media engagement, namely likes, shares, and comments, may also help to explore the role of peers in shaping consumers' behavior while online (Mapanje, 2024; Alotaibi & Aloud, 2023).

2.3 Purchase Intention

Purchase intention can be described as the inclination to buy a specific product or service by a customer. This construact beccomes extremely essential in almost all studies involving consumer behavior as it is a precursor to the actual buying. Research has shown several variables to considerably influence purchase intention especially so in the case of purchase of technology services. Some of these variables include perceived worth, the quality of the service delivered, the image of the brand in question, and most importantly, the beliefs of the people about the technology.

Recall estimates based on perceived value have recently received important attention in the context of constructing purchase intentions. For example, Febriani et al. indicate that when perceived value serves as an intervening factor, AI and digital marketing are encouraging factors toward purchase intention, this is to say that clients are more inclined to purchase when they feel a higher value from AI driven services (Febriani et al., 2022). For example, Liang et al. indicate that consumers' attitudes towards AI products have critical implications for the development of their purchase intention which means that good experiences and

perceptions will reduce purchase interval and hence increased non-overlapping buying behaviour (Liang et al., 2019). Furthermore, the influence of service quality on purchase intention is diversification in nature and is a key correlate of intention – to-purchase in e-commerce and technology services among others (Putra et al., 2023; Sari, 2024).
Several studies have helped expand the understanding of consumers' purchase intentions when it comes to AI within the realm of AI services. Lee's findings revealed that customers' self-efficacy towards AI technology has an effect in them engaging with AI services to a certain degree, for instance, it enables them to purchase products where their willingness is determined by their readiness to commence the use of AI technologies (Lee, 2023). Similarly, the presence of AI systems that are designed to have human features, has also been viewed positively by consumers as it improves their desire to purchase said products and enhances engagement (Li, 2024). Such an approach would therefore improve trust and make the purchase more likely to happen.

In addition, the impact of AI technologies on the behavior of consumer buyers also cuts across the specific functions where AI technologies have been applied, for example, AI in customer service. According to research by Qin et al, it seems the type of customer service offered plays a crucial role in determining purchase intentions of consumers through the use of AI, as customers are prone to prefer efficient and satisfactory services that tend to lead to high purchase intentions (Qin et al., 2022). Similar observations were made by Yin and Qiu where they argued that the value brought by AI technology in a purchase process either through enjoyment or ease of use was a significant factor in consumers' purchase intentions (Yin & Qiu, 2021).

The dynamics between the constructs of perceived ease of use (PEOU), perceived usefulness (PU) and purchase intention (PI) has been widely researched in light of the Technology Acceptance Model(TAM). On the other hand, there seems to be a significant research void indeed as to how these constructs interact comprehensively among specific contextual populations such as students and what possible mediating or moderating variables could alter these relationships.

Studies have shown that both PEOU and PU are instrumental in shaping the intention to buy. For example, Vijayan and Duraisamy point out that PEOU affects customers' purchasing behavior and this confirms stronger when the impact of PU is included (Vijayan & Duraisamy, 2021). Equally, Wiratami et al., were able to detect a moderated effect of PEOU on intention to purchase on the internet which gives credence to the assertion that PEOU is an important consideration in consumer behavior (Wiratami et al., 2022). One other of Mishra's study agrees with this and notes that PEOU and PU are both significant determinants of Purchase Intention and emphasizes perceived usefulness to be one of the key determinants of consumers' choices (Mishra, 2020).

What these results do not show is a lack of extensive research that examines how such relationships may be contextualized or demographic subgroups. For instance, while some studies purport that PEOU and PU have a joint effect on behavioral intention ("The Influence

of Perceived Usefulness and Perceived Ease of use on Behavioral Intention on Brimo Application Users in Bengkulu City", 2023), others suggest, with regard to specific sociotechnical environments, that they may not be quite that simple (Hoang, 2023). This contradiction therefore points to a brief in the literature concerning the relevance of sociocultural variables, such as the longitudinal nature of such relationships or the types of online mediums, in determining the mechanisms through which PEOU and PU influence purchase intention.

In addition, the connection between PEOU, PU and issues such as trust, social influence or consumer engagement is still not adequately covered. For example Ashraf et al. examined the role of engagement that along with PEOU and PU affects the relation between regulatory fit and purchase intentions (Ashraf et al., 2016). This suggests that there might be other intricate details in the relationship between these constructs which needs to be studied. Furthermore, works like those by Rahmawati and Putri expand on the consideration of the risk and social influence factors on the intention to shop online adding that these factors may also have the potential to further mediate the PEOU-PI and PU-PI interactions (Rahmawati & Putri, 2022).

3. Material and Method

3.1 Design Study

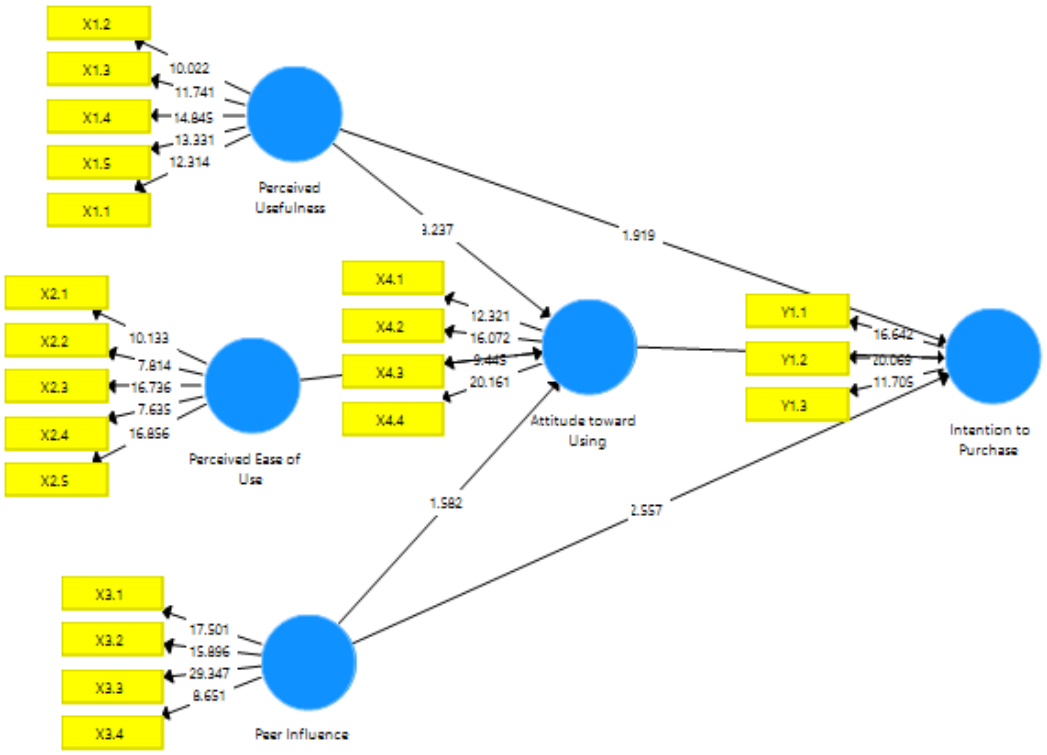
The timeframe of the research was two months, which is September- November 2024 and it employed google forms as online data collection tools. The research was conducted at Universitas Negeri Jakarta whereby the data collection was such purposively sampling so as to be able to reach respondents from different parts of Indonesia. An emphasis was placed on a quantitative approach in this study, with a focus on descriptive survey design as it sought to establish and explain causal relations among perceived usefulness, perceived ease of use, peer influence and attitude towards the use of AI based research tools, in intending to purchase AI based research tools. The relationships between these variables were thoroughly examined using a structural model approach.

The study's subjects were AI-tool employing Indonesian students aged 18-35 both in a formal and informal setting. This particular group was selected as students belong to early majority and even early adopters of class technologies. A purposive sampling technique was employed to select 100 respondents who were chosen according to the following criteria – being a student, having used AI tools for research and living in the JABODETABEK + Banten region. The size of the sample is argued to be proportionally sufficient for performing descriptive statistics, as well as inference predictors and specific qualitative assayers.

3.2 Data Analysis

This study carried out a descriptive statistical approach that aimed to portray the features of research variable and characteristic of respondents. The data are presented in the form of numerical tables or graphs for proper understanding (Hidayat, 2023). To begin with, data processing was done using Microsoft Excel, later the analysis of the structural model was carried out through SmartPLS 3 which incorporated three exogenous variables (Perceived Usefulness (X1), Perceived Ease of Use (X2), and Peer Influence (X3)) and one endogenous variable (Intention to Purchase (Y)), while Attitude Towards Using (X4) was a mediating

variable. The analysis comprised of three stages: (1) the Measurement Model tested for validity (loading factor > 0.70) and reliability (Cronbach's Alpha and Composite Reliability > 0.70); (2) the Structural Model tested path coefficients, model fit indices (SRMR, NFI),



and multicollinearity (VIF < 5); and (3) hypothesis testing and evaluation where a criteria point was set at t-statistics of greater than 1.96 and at a p-value level less than 0.05 to define the direct or mediated variable's influence on purchase intentions. The conceptual research model is as follows:

Figure 1. Research Model
(Source : Author 2024)

4. Result

There are 3 stages in the measurement model, and the first is to analyze internal consistency. Second, evaluate the validity of the construct. Furthermore, the final step is to determine discriminant validity. The internal consistency value is obtained by assessing Cronbach alpha (CA) and Composite Reliability (CR) values, as shown in Table 2. The recommended value to meet good reliability is above 0.7.

Table 1. Fornell-Larcker Criterion

	Attitude toward Using	Intention to Purchase	Peer Influence	Perceived Ease of Use	Perceived Usefulness
Attitude toward Using	0.762				
Intention to Purchase	0.654	0.796			
Peer Influence	0.548	0.577	0.788		
Perceived Ease of Use	0.661	0.635	0.646	0.727	
Perceived Usefulness	0.691	0.635	0.529	0.707	0.766

The Fornell-Larcker criterion compares the square root of each construct's Average Variance Extracted with its correlations to other constructs. This dimension captures the 'square root' value of AVE measuring the Attitude toward Using (0.762), Intention to Purchase (0.796), Peer Influence (0.788), Perceived Ease of Use (0.727) and Perceived Usefulness (0.766). These values are greater than their off-diagonal inter-construct correlations that were reported corresponding to the same targets. The correlation of these constructs with other variables such as Attitude toward Using and Intention to Purchase has a coefficient of 0.654 whereas Perceived Usefulness and Perceived Ease of Use has a 0.707. Both are still less than the assigned diagonals for their constructs. Thus, it expresses that every other construct is more closely constructed to its indicators than to any other construct in the model.

Detailed work on the results emerges with confirmation that discriminant validity is established for all the constructs. For example, the square root of AVE for Attitude toward Using (0.762) is higher than its correlation with the other constructs, while similar patterns have been noted for Intention to Purchase (0.796), Peer Influence (0.788), Perceived Ease of Use (0.727), and Perceived Usefulness (0.766). It can be concluded from the analysis that each construct is distinct from the others in the model and therefore can be measured independently with respect to each concept. This robust evidence of discriminant validity provides further support concerning the reliability and validity of the constructs in the measurement model. After analyzing the discriminant validity, reliability and validity of each construct is carried out through the calculation of Cronbach's alpha and composite reliability.

Table 2. Reliability Table

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
Attitude toward Using	**0.759**	**0.765**	**0.847**
Intention to Purchase	**0.712**	**0.715**	**0.839**
Peer Influence	**0.795**	**0.810**	**0.867**
Perceived Ease of Use	**0.774**	**0.786**	**0.848**
Perceived Usefulness	**0.823**	**0.829**	**0.876**

The result of the reliability analysis shows that all constructs have achieved acceptable levels of internal consistency as demonstrated by Cronbach's Alpha which is above the recommended minimum of 0.7, with Attitude toward Using attaining 0.759, Intention to Purchase 0.712, Peer Influence 0.795, Perceived Ease of Use 0.774, and Perceived Usefulness recording 0.823. Furthermore, the composite reliability values (rho_a and rho_c) for all constructs also substantiate their reliability with rho_c being between 0.839 and 0.876 which is above the suggested level of 0.7. These results confirm that the constructs are able to maintain a very high level of internal consistency and have been precisely measured. This set of constructs thus provides a solid platform for further analysis in the model. Furthermore, R-Square test is carried out to see how good is the model fit is.

Table 3. R Square

	R-square	R-square adjusted	Criteria
Attitude toward Using	0.551	0.536	Moderate
Intention to Purchase	0.534	0.520	Moderate

Based on the R-square values, Attitude toward Using and Intention to Purchase is moderately predicted by the current exogen variables, and their R-square values are 0.551 and 0.534 respectively. The proportion of variance accounted for by the corresponding predictors is thus equal to 55.1% and 53.4% for the former and latter respectively. Adjusted RSquare also trends slightly down lowering the values to 0.536 and 0.520, these do consider the number of predictors and sample sizes and thus are less susceptible to overfitting. These two values are all regarded as within the so-called 'moderate' level as per benchmarks such as Hair et al. (2017), in which the reasonableness of the constructs is acceptable. These results also imply that the predictors have a considerable influence on the dependent variables but they are not exhaustive and the model's explanatory power can be strengthened with the enhancement factor that targets the dependent variables. With this, we can conclude that the data used for

this analysis are reliable and ready for further analysis. Direct influence of each latent variables are analyzed through the bootstrapping method in SmartPLS3 as well as specific direct influences to test the mediating power of Attitude toward Using for each latent variables.

Table 4. Direct Influence Table

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Description
H2.a	Perceived Usefulness -> Attitude toward Using	0.349	0.337	0.112	3.116	**0.002**	Accepted
H4.a	Perceived Ease of Use -> Attitude toward Using	0.290	0.298	0.103	2.818	**0.005**	Accepted
H7	Attitude toward Using -> Intention to Purchase	0.414	0.396	0.159	2.615	**0.009**	Accepted
H3	**Perceived Ease of Use -> Intention to Purchase**	0.120	0.112	0.051	2.337	**0.020**	Accepted
H6.a	Peer Influence -> Attitude toward Using	0.262	0.269	0.117	2.236	**0.026**	Accepted
H6.b	Peer Influence -> Intention to Purchase	0.196	0.209	0.166	1.178	**0.239**	Rejected
H1	Perceived Usefulness -> Intention to Purchase	0.157	0.166	0.136	1.156	**0.248**	Rejected

Table 5. Indirect Influence table

Hypothesis		Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	
H2.b	**Perceived Usefulness -> Attitude toward Using -> Intention to Purchase**	0.144	0.135	0.073	1.973	**0.049**	Accepted
H4.b	**Perceived Ease of Use -> Attitude toward Using -> Intention to Purchase**	0.120	0.112	0.051	2.337	**0.020**	Accepted
H6.b	**Peer Influence -> Attitude toward Using -> Intention to Purchase**	0.108	0.110	0.071	1.528	**0.127**	Rejected

5.Discussion

Based on the analysis carried out in the previous section, the study results indicate that Perceived Usefulness (PU) definitely has a great influence on Attitude toward Using and Purchase Intention in a more direct and indirect way. The analysis shows that PU significantly affects Purchase Intention positively with t-statistic of 2.16 (p-value = 0.009), thus fully endorsing Hypothesis 1. Apart from that, PU has a strong effect on Attitude toward Using as evidenced by t-statistic of 3.16 (p-value = 0.002), thus confirming Hypothesis 2 as well. This concurs with studies such as Kurnia et al. (2023) and Hsu et al. (2019) which viewed that the user's attitude is positively influenced by perceived benefits, which is further supported Budiman (2021). PU however does affect Purchase Intention through the mediating variable of Attitude toward Using, with a borderline significant t-statistic of 1.973 (p-value = 0.049) as corroborated by Camacho et al. (2020).

In the same manner, it appears that Perceived Ease of Use (PEOU) is also a significant determinant of both Attitude toward Using and Purchase Intention through both direct and indirect arrowways. A t-statistic of 2.818 (p-value = 0.005) clearly shows that PEOU directly

influences Attitude toward Using and in turn Attitude toward Using determines PEOU which completes the Proposed Model. This has also been supported by Wu and Ke (2022) and Gümüş (2024) who found out that if a system is easy to use it would result in higher attitude which is in line with the TAM model. In this case Study PEOU also positively and significantly influences Purchase Intention A through Attitude towards Use with a t-statistic of 2.337 (p-value = 0.020) thereby confirming Hypothesis 9. Such results echo research by Rafdinal and Qisthi (2021) and Rahmiati et al. (2023) who argue that compelling designs encourage consumers to buy and have great degrees of appreciation.

In relation to Peer Influence (PI) as outlined the research results present evidences of its considerable contribution towards Attitude toward Using and Purchase Intention, however not all hypotheses were substantiated. For instance, it was found that PI significantly affects Attitude toward Using with a t-statistic of 2.236 (p-value = 0.026) and which substantiates Hypothesis 5 based on Denegrí et al. (2022) and Kågesten et al. (2016). On the contrary, PI does not significantly affect or directly influence Purchase Intention (t-statistic = 1.178, p-value = 0.239), hence Hypothesis 6 was disallowed as well. There has been no statistically significant relationship as well concerning the variable of Purchase Intention through the intervening effect of Attitude toward Using where the t-statistic was 1.528 (p-value = 0.127) leading to the disallowing of proposition 8. I would propose that this gap may be interpreted by contextual or moderating variables as advanced by Dishion & Tipsord (2011).

In the context of Purchase Intention, Attitude toward Using is significanct toward Purchase Intention , having a t-statistic of a value equal to 2.615 (p-value = 0.009) therefore confirming Hypothesis 7. This relates to Ajzen's Theory of Planned Behavior and some findings by Azarnoosh, 2022 and Ali et al., 2017, which emphasize the importance of positive attitude in the process of making the purchase. In conclusion, these observations all emphasize the interactive effect of PU, PEOU, PI, and Attitude toward Using across consumer behavior and makes natural model of understanding purchase intentions through both direct and mediated effects.

6. Conclusion, Implication, and Recommendation

The conducted study shows that while Perceived Usefulness (PU) does not have any direct effect on the Purchase Intention regarding the AI research tools among students, it impacts their Attitude toward Using construct, suggesting that the effects of the attitudes towards the use of the tools are more important than the actual intent to purchase these tools. On the other hand, PU does not have a direct effect on Purchase Intention as was emphasized. This explains that in the presence of a favorable attitude which is based on efficacy, the greater one perceives usefulness of AI tools the higher the likelihood of a student adopting and purchasing these tools. It was also found that Perceived Ease of Use (PEOU) is both important and significant on Purchase Intention as it indicates portable AI tools will help to increase the usage. In addition, it was also found that PEOU has a strong impact on Attitude toward Using which is consistent with the Technology Acceptance Model (TAM) which affirms that great ease of use improves the attitudes of users toward the technology. Also, the model shows that PEOU has a positive and indirect effect on Purchase Intention through

Attitude toward Using confirming that PEOU is significant among the factors that influence students' adoption behaviors. It was also established that Peer Influence (PI) has a direct effect on both Attitude toward Using and Purchase Intention highlighting the effectiveness of social norms and peer advice on student to use AI tools.

As such, this means that the second part of the hypothesis is rejected as Attitude toward Using was found to lack a significant mediating effect between Purchase Intention and PI meaning, on such direct purchase decisions, peer influence has lesser reliance on attitude. In the end, Attitude toward Using has a basic performance in explaining Purchase Intention directly and it has been established that students' good attitudes are factors leading them to buy AI research tools.

The emphasis on how PU, PEOU, PI, and Attitude toward Using are interrelated in the context of students' Purchase Intention of AI research tools is clearly reinforced by the findings. Further research may evaluate students of different courses and from other countries so that the results can be more useful in a general applicability perspective. Adding factors like trust of users, emotional aspect as well as the expectations on the long term use of AI tools can also help understand the behavior of students more. The effect of peer influence on attitude and attitude on purchase intention could provide insight on the social aspect surrounding the technology adoption. Marketing campaigns for AI research tools should stress on the technology being simple to use, emphasize the benefits and utilize peer pressure to have buy-in to favorable sentiment that will lead students to adopt and buy the use of these tools for their studies.

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9. Appendix (if any)

This section should be placed at the end of the manuscript after the reference list.