Switching Intentions of Bangladeshi University Students Between Different AI Tools: A Push–Pull–Mooring Perspective

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Approval

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Declaration

I hereby declare that this thesis has been completed under the supervision of **Ms. Tapushe Rabaya Toma, Assistant Professor** , Department of Software Engineering, Daffodil International University. I also affirm that this thesis is my original work, submitted for the degree of B.Sc. in Software Engineering, and neither the entire work nor any portion has been previously submitted for another degree at this or any other university.

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Abstract

The purpose of this study is to investigate Bangladeshi university students' switching intents between different AI tools using the Push-Pull-Mooring (PPM) paradigm to discover psychological, social, and contextual aspects that influence their decisions. The study aims to investigate how push factors (e.g., poor trust), pull factors (e.g., ease of use, social impact), and anchoring factors (e.g., switching costs) combine to influence switching behavior. 350 students participated in a self-administered survey using validated measurement scales as part of a quantitative research approach, and 320 valid responses were obtained. To verify the validity of the measurements and test the suggested correlations, we performed Partial Least Squares Structural Equation Modeling (PLS-SEM) on the data using SmartPLS. The findings show that the most important factors influencing switching intention are perceived value, trust, social influence, and switching benefits; ease of use has a significant but smaller impact. Significant perceived benefits can overcome switching costs, which act as a barrier. The results show that in this setting, students' decisions to switch are a dynamic mix of how useful the technology is, how much their peers influence them, and how sure they are of their choice. This is in line with the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) of the PPM framework. This research enhances theoretical frameworks by integrating PPM and technology adoption constructs, while also offering pragmatic guidance for AI developers and educators on enhancing trust, usability, and perceived value to facilitate sustained adoption and prevent unnecessary transitions.

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CHAPTER 1: INTRODUCTION

1.1 Background

The fast development of AI technologies has resulted in the appearance of a variety of AI-based learning tools. University students have more and more opportunities to use to facilitate their studies with the new range of tools that are available. This richness has led to a culture of high switching where learners exhibit a tendency to switch between AI tools to suit their learning requirements. Nevertheless, this has mostly underperformed the scope and the internal processes that drive such switching activities among the Bangladeshi university students. To fill this gap, the current research will analyze the occurrence of active switching between AI tools among Bangladeshi students and, in that case, determine the major aspects of this behavior. The study utilizes the Push-Pull-Mooring (PPM) framework initially formulated based on the migration theory that has been extensively utilized to elucidate switching behavior in various settings, such as adoption of technology and migration (Bansal, 2005). In this context, mooring factors are those personal or situational constraints that may facilitate or inhibit switching; push factors are the weaknesses of the existing tools which make students want to leave; and pull factors are the attractive properties of alternative tools which make students adopt (Zhou and T., 2024). The use of the PPM model can enable this study to examine the psychological, social, and context factors underlying the intentions of students to switch. The push factors may involve doubts about the accuracy or reliability of the works of the current AI tools, which will force students to find alternatives in the context of Bangladesh (Mariska, 2022). On the other hand, the pull factors might be the increased usability, better performance, or an extended variety of functions compared to alternative platforms (Davis, 1989; Yang, 2004). Also, social pressure, such as peer suggestions and the current trends in academia, is an important factor affecting attitudes and inspiring students to make a change. Push and pull factors can be mitigated through switching-related variables, which includes the time and effort to master a new tool and the perceived rewards of switching which may reinforce or undermine switching intentions (Bansal, 2005; Liu, 2006). Positive perceptions of alternative AI tools significantly impact switching intentions (Ajzen, 1991). Our study integrates these variables to illustrate the complex interplay of factors influencing AI tool switching behavior among Bangladeshi students, transcending fundamental cost-benefit analysis.

1.1.1 AI in Education

AI is now an important part of modern education, changing the way people teach and learn all over the world. AI technologies allow for personalized learning, automatic grading, smart tutoring, and adaptive feedback, all of which make students more interested in learning and improve their results. The COVID-19 pandemic has sped up the use of AI, making schools around the world use digital tools for remote learning (Hasan, 2023). AI-powered programs like intelligent tutoring systems, plagiarism detection software, automated essay scoring tools, and chatbots help students all over the world with their schoolwork. Students often have problems with trust, usability, and relevance, which makes them unhappy and less likely to use these technologies again, even though they are becoming more widely available. Consequently, students frequently switch between AI platforms to locate tools that optimally align with their academic goals and preferences (Mariska S. R., 2022). These dynamic stresses the importance of looking into the things that affect AI tool switching so that developers can make platforms that are easy to use and trustworthy, and teachers can use AI correctly in the classroom.

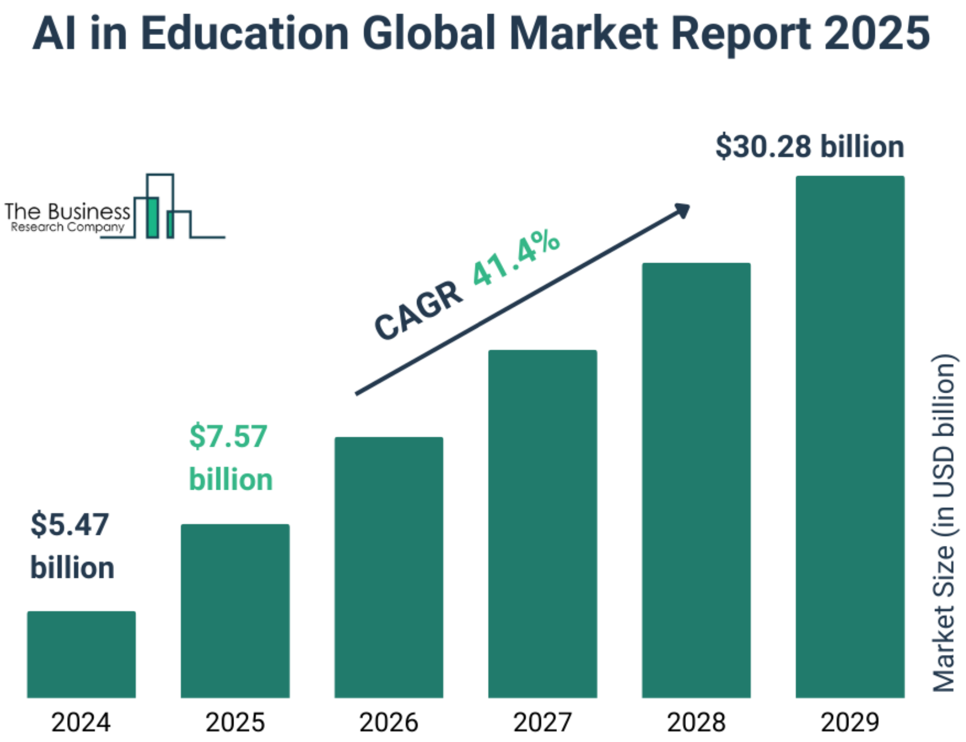

Figure-1.1: AI in Education Global Market Report (Company, 2025)

1.2 Situation of Switching Between Different AI Tools

1.2.1 Global

People who use technology around the world are becoming more willing to switch between AI products because they are unhappy with the ones they already have or because they are drawn to better ones. Research on technology switching behavior shows that push factors like poor system performance, lack of trust, and dissatisfaction make people leave their current platforms (Bansal, 2005). Users are drawn to new technologies by things like how easy they are to use, how well they work, and how well they are endorsed by others (Davis, 1989; Yang Z. &., 2004). Peer recommendations and community trends significantly affect user attitudes towards the development of AI products (Venkatesh V. M., 2003), underscoring the global significance of social influence. The ease of migration is affected by things like how much work it takes to switch and how often people use the current platforms (Liu A. H., 2006). Users think about the pros and cons of switching before they make a decision, so these factors are very important for understanding how switching works.

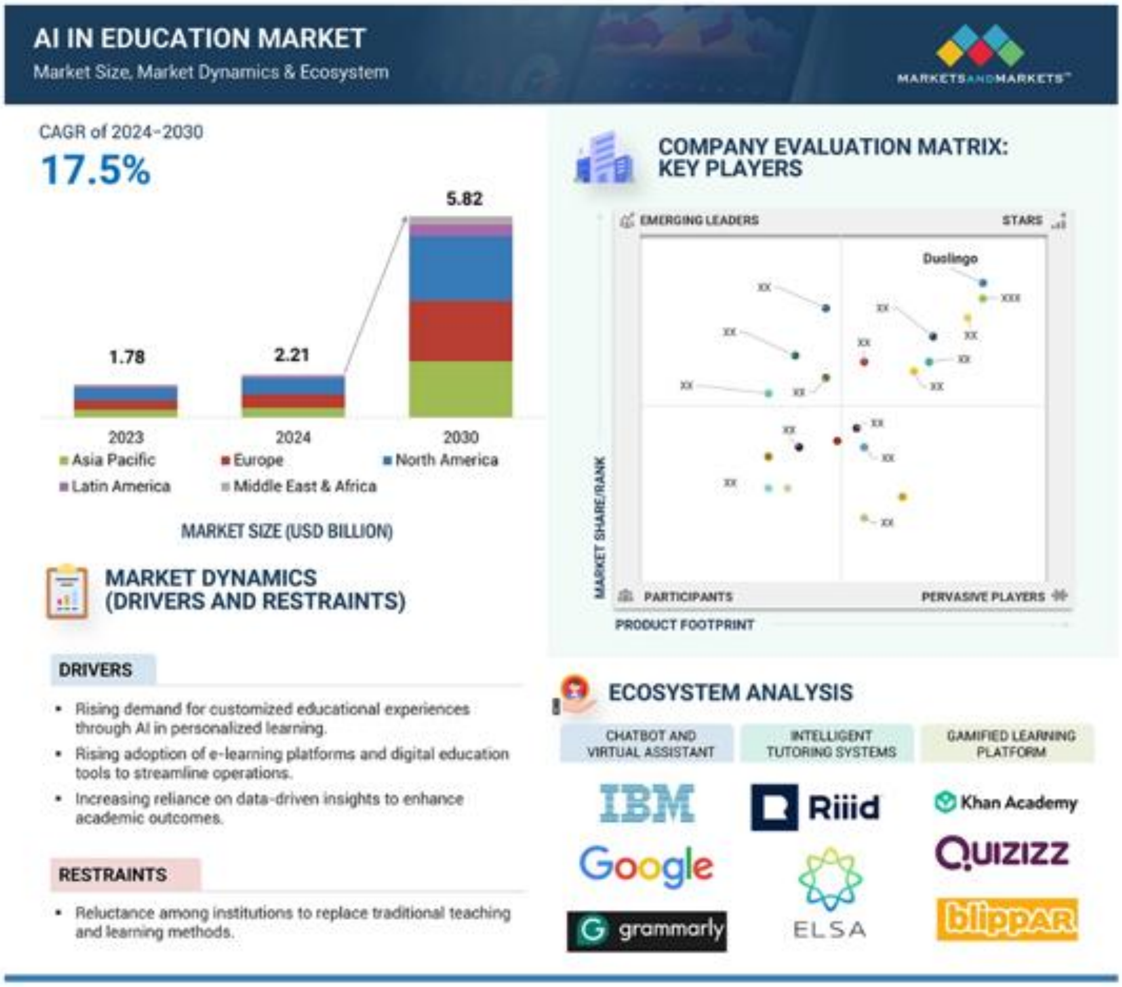

Figure-1.2: Global AI Adoption (marketsandmarkets, 2025)

1.2.2 Bangladesh

The use of AI tools in education is growing in Bangladesh, especially among university students. These students use AI platforms for a lot of schoolwork, like translating languages, helping with research, and making content. However, the switching behavior of Bangladeshi students has not been comprehensively examined. In Bangladesh, there are a number of contextual factors that affect the switch to AI tools.

Students want to switch because they don't trust the AI tools they already have, they don't know how to use the new platforms, and their internet connection is limited (Mariska S. R., 2022). Social influence is particularly potent in Bangladeshi academic environments, where peer endorsements and communal norms significantly shape technology selections (Venkatesh V. M., 2003). Also, switching costs, like the time and effort it takes to get used to new AI tools, are big problems (Bansal, 2005; Liu A. H., 2006).

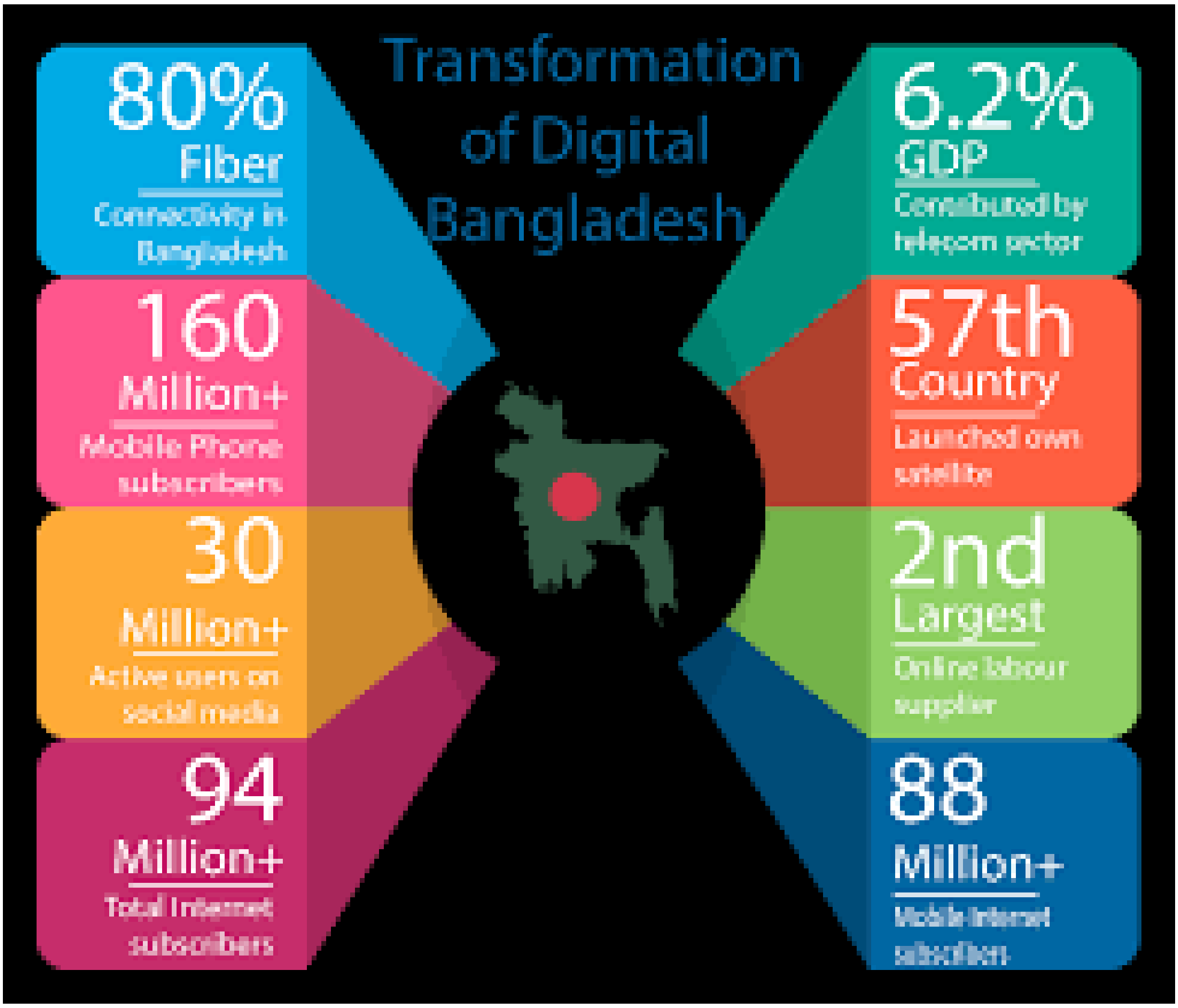

Figure-1.3: Bangladesh AI Adoption (ICTD Portal, 2024)

1.3 Research Problem Statements

Because there are so many AI tools available, students choose the ones that are most useful, easy to use, and relevant to their needs. Functionality makes sure that the tool can do the tasks it needs to, like helping with writing, analyzing data, or coding. Ease of use is also very important because students like products that are easy to understand and don't take long to learn. Relevance is important because different academic goals exist. A student who is doing research might choose summarization or citation tools, while a programmer might choose AI coding helpers. Cost, compatibility, and how well it works with other platforms all play a role in making decisions. Finally, students pick AI tools that are useful, simple, and efficient, which helps them get more done, learn better, and keep up with the changing needs of education.

1.4 Research Questions

1 Do social influence and ease of use effect switching intention to use AI?

2 Do attitude habit and trust influence switching intention to use AI?

3 Do Perceived value influence students switching intention to use AI?

1.5 Research Objectives

1 To identify the effect of social influence and ease of use in the switching intention to use AI.
2 To identify the effect of Attitude, habit, and trust influence in the switching intention to use AI.
3 To identify the effect Perceived value influences students in the switching intention to use AI.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

The Push-Pull-Mooring (PPM) model describes switching behavior in terms of three primary elements, namely mooring factors, which determine how easy or difficult the shift is; pull factors, which encourage people to switch to an alternative option; and push factors, which encourage them to leave their existing choice (Krishnan, 2024). This model is actively used by scholars in order to analyze the consumer intents to switch between various technologies.

2.2 Theoretical Framework

The Push-Pull-Mooring (PPM) model, initially derived from migration theory, has been widely employed across various industries—including technology, banking, travel, and entrepreneurship—to explain why consumers switch brands (Krishnan, 2024; Jung, 2017; Yoon, 2021; Lai, 2012; Ojiaku, 2018). The model conceptualizes three forces influencing switching behavior: push factors, which reflect the negative aspects of the current product or service; pull factors, which highlight the advantages of alternative options; and mooring factors, which encompass personal or contextual constraints that hinder change. By accounting for both motivating and inhibiting forces, this comprehensive framework enables a more thorough analysis of consumer switching behavior.

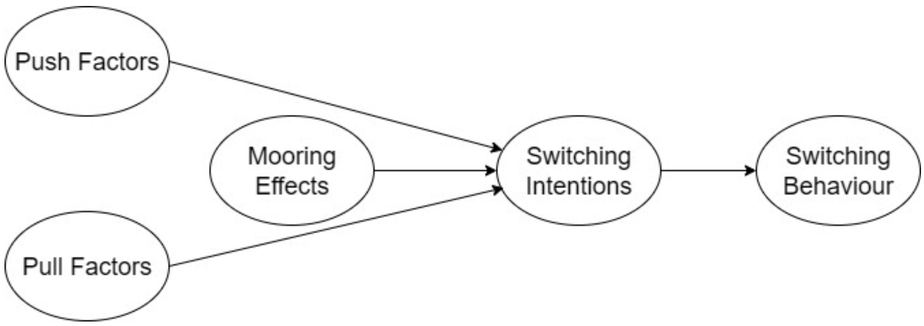

Fig-2.1: Push Pull Mooring Model

Push factors refer to elements of a service that generate dissatisfaction or negative perceptions among users. In the context of this study, trust serves as a key motivating factor. When users question the reliability, security, or overall integrity of their current AI tool, they become more inclined to switch to alternative options (Krishnan, 2024). This is in line with what has been found before in the airline industry, where travelers switched to other carriers because they didn't trust them and the service was bad (Jung, 2017), and in internet-only banking, where customers switched to better options because they weren't happy with the ones they already had (Yoon, 2021). Such bad experiences reduce customer pleasure and increase psychological pressure to seek alternatives.

Pull factors are good characteristics of an alternative service that entice users to switch. In this study, convenience of use and social influence operate as pull factors. A platform with improved usability requires less cognitive and time investment to run, making adoption more appealing (Krishnan, 2024; Lai, 2012). Similarly, social influence derived from peer recommendations, industry trends, or observable popularity can be a powerful magnet (Ojiaku, 2018). In mobile shopping, ease of use and peer endorsement have been demonstrated to induce customers to switch from traditional retail to mobile platforms (Lai, 2012). Similarly, in the entrepreneurial setting, social and environmental factors positively influenced people's inclinations to start new businesses (Ojiaku, 2018). These pull pressures show in AI tool usage when students see classmates successfully adopting a different platform or when a competitive tool has a more intuitive, user-friendly interface.

Mooring factors are personal, societal, or structural characteristics that serve as barriers or facilitators in the switching process. Even when there are substantial push and pull forces, large switching costs the time, effort, and resources required to move platforms can discourage switching (Krishnan, 2024). (Jung, 2017) discovered that loyalty programs and cumulative rewards acted as anchoring factors, preventing customers from switching despite appealing alternatives. In a similar vein, (Yoon, 2021) discovered that switching costs reduced the correlation between dissatisfaction, peer pressure, and plans to switch to online-only banks. (Lai, 2012) found that perceived risk and switching costs reduced the impact of convenience and enjoyment on consumer migration decisions in mobile purchasing. Significant switching costs in educational settings could include the need to transfer data, retrain processes, or adjust to a new user interface, which would make students less likely to replace their current AI tool. To sum up, the PPM framework provides a systematic way to categorize the variables in the study: switching cost corresponds with mooring considerations, ease of use and social influence correspond with pull elements, and trust corresponds with push factors. Empirical evidence from a variety of contexts supports this classification (Krishnan, 2024; Jung, 2017; Yoon, 2021; Lai, 2012; Ojiaku, 2018). This paradigm recognizes the interplay between dissatisfaction, attraction, and contextual barriers, providing a thorough understanding of why college students switch between AI tools.

2.3 Ease of Use

Ease of use (Davis, 1989) is the degree of convenience and non-strain that one will have when operating a certain technology. The Technology Acceptance Model (TAM) postulates that perceived usefulness and ease of use are major factors that would influence an individual to welcome new technologies (Davis, 1989). According to the model, users tend to believe in a technology when it is easy and simple to use despite the fact that it has limited functional abilities (Venkatesh et al., 2000). Indicatively, Venkatesh et al. (2008) observed that cognitive load and learning demands are minimized with simplification of technology and consequently the resistance to adoption will be minimized. On the same note, Gefen (2003) also pointed out that ease of use makes the user trust and encourages further interaction with e-services and this is also a key aspect in the user experience design. Professionally, including health care, Chau (2002) discovered that usability had a significant impact on the rate of system utilization and general satisfaction. Studies also show that ease of use is critical especially on mobile and AI-based applications as it is positively related to the intentions of consumers to further adopt and experiment with new tools (Zhou, 2011). Lee et al. (2003) opined, as well, that technology ease influences the rate of adoption, as well as chances of continued usage. Lastly, research has indicated that the user is more likely to change to a system that is perceived to be easy to use than the perceived complex system, thus, a close relationship between user-friendliness and switching intentions (Kim, 2007).

2.4 Social Influence

Social influence is a concept used to determine the extent to which significant individuals in their lives persuade them to use certain technologies or behaviors (Ajzen, 1991; Venkatesh et al., 2000). Mechanisms that help people conform, identify, and internalize the attitudes and behavior of others lead to individuals often aligning their attitudes and actions with those of others (Kelman, 1958; Venkatesh et al., 2000). In the past literature, social influence has been found to be critical in influencing the adoption and use of technology and information systems (Malhotra, 1999; Venkatesh et al., 2000). As an example, the Technology Acceptance Model 2 (TAM2) includes the social influences through subjective norms and voluntariness, which shows that the model influences the perceptions of usefulness and intention to use technologies among users (Venkatesh et al., 2000). In addition to adoption, social influence has a huge impact on switching behaviour between different technologies, platforms, and services

(Chang, 2014; Zhou, 2022). Zhou (2022) particularly discovered that, social influence does not merely directly influence user intentions to change the social media platform but also mediates the relationship between dissatisfaction and the switching intentions. Also, word-of-mouth communication and peer pressure are crucial in the process of decision-making. Wangenheim (2004) found out that credibility and similarity of the communicators play an important role in decision made by the users when changing the service provider. The role of social identity and necessity to belong in technology adoption and switching are also emphasized in research. In a study, Cheung (2010), discovered that the actions of users on the social media are usually influenced by the group goals that are based on their personal beliefs and group identification, which indicates that people can use new technologies or even change the platforms to ensure they can remain socially aligned and belonging.

2.5 Attitude

Attitude is a common term in psychology and behavioral research and describes the positive or negative judgment of a certain behavior or activity made by a person (Ajzen, 1991). It is one of the most critical factors that determine the choice of consumers to adopt, use, or re-adopt new technologies (Fishbein, 1977). The Theory of Planned Behavior (TPB) states that the attitude of an individual toward any certain issue is influential in determining the future behavior (Ajzen, 1991). Users tend to interact with technology systems that they feel useful, enjoyable or beneficial (Venkatesh et al., 2003). The empirical evidence continues to indicate that the attitude towards a technology is positive, which increases the chances of adoption and transition. Indicatively, Alalwan (2016) established that the customers who had positive perceptions of mobile banking services showed a higher tendency to remain involved or migrate to better versions. In the same way, perceptions of a platform, including reliability, efficiency, or trustworthiness, can strongly affect students in either continuing to use the existing tool or switching to a more productive one with the help of AI tools (Dwivedi, 2021). Such an attitude is not just more satisfying but also proactive to users who are willing to replace the more advanced AI systems (Shin, 2021).

2.6 Trust

Trust is a fundamental psychological construct that signifies an individual's confidence in the reliability, integrity, and competence of another person or institution (Mariska S. R., 2022). It greatly affects how customers act, especially when they are unsure or face risk, like when they have to choose between competing brands or technologies (Han H. &., 2013). Trust reduces the perceived risk of making a decision by assuring that the selected option will meet expectations and deliver the promised advantages (Yen Y. X., 2010) . It is an important factor that affects consumer happiness and loyalty, affecting long-term commitment and making it less likely that they will switch suppliers or products (Hauff, 2019). In online and technology-mediated environments, trust encompasses views about system security, privacy, and information veracity, all of which influence users' acceptance and continued usage intentions. For example, in social networking platforms, trust increases both users' switching intentions and actual switching behavior by mediating perceived risks and benefit (Lin C. N., 2017). Similarly, in the banking industry, trust has a major impact on switching intentions by mediating the relationship between customer pleasure and loyalty (Putra, 2019). Customer trust can reduce the negative impact of perceived switching costs and boost retention even when other options are available (Liu C. T., 2011). Trust is also important in shaping user attitudes toward AI-based products and platforms, as the perception of reliability and ethical usage influences uptake and retention (Cheng, 2022). Users who trust an AI system are more likely to interact with it and less likely to switch to competing technologies (Cheng, 2022). From a relationship standpoint, trust arises from consistent pleasant experiences, effective communication, and expectation fulfillment, all of which contribute to a strong foundation for consumer loyalty (Carter, 2014). Brand image, company reputation, and perceived product quality can all have an impact on trustworthiness (Ceesay, 2017). Furthermore, trust mitigates the influence of satisfaction on switching intentions by ensuring customers that their preferred supplier will continue to meet their needs, lowering uncertainty about future transactions (Antón C. C., 2007).

2.7 Switching Benefit

Switching benefits are the perceived advantages or value that consumers expect to acquire when switching from one service or product provider to another (Kim H. W., 2010). These benefits function as "pull" factors, attracting customers to a new alternative and frequently outweighing their loyalty to the present provider (Bansal, 2005). Switching benefits in digital product and service contexts, such as e-commerce, may include enhanced usability, lower pricing, or better features (Msaed, 2017). Smartphone customers, for example, may switch brands because the new phone provides emotional gratification, social prestige, or novel features that their existing phone does not (Wong, 2019). These advantages can dramatically boost switching intentions, even when switching costs are present (Kim H. W., 2010). In fact, when the perceived value or benefit of the alternative supplier is significant, consumers frequently justify the effort or cost of switching (Lu T. T., 2011). Research has also demonstrated that switching benefits extend beyond observable or technical improvements. Switching benefits include psychological and symbolic qualities such as novelty, personal growth, and greater identity expression (Wong, 2019). In the retail industry, migrating from physical to online storefronts is frequently motivated by benefits such as convenience, lower prices, or a wider product selection (Roy Dholakia, 2002). These advantages may offset emotional attachment or inertia to traditional retailers (Bansal, 2005). Finally, switching benefit is an important incentive in consumer behavior models, functioning with happiness and perceived value to determine whether a client remains loyal or switches suppliers (Kim H. W., 2010; Msaed, 2017; Lu T. T., 2011).

2.8 Switching Cost

Switching cost is the perceived or actual cost that a consumer incurs when switching from one service provider or product to another, and it encompasses more than simply financial charges (Burnham T. A., 2003). These costs are divided into three categories: procedural costs (such as time and effort), financial costs (such as cancellation fees), and relational costs (such as emotional attachment or trust), all of which work together to dissuade customers from switching providers (Burnham T. A., 2003). In the context of business services, switching costs act as departure barriers, based on perceived economic and relational value, resulting in long-term loyalty (Liu A. H., 2006). Furthermore, switching costs frequently serve as a mediator in the link between customer satisfaction, perceived value, and loyalty, implying that even when customers are content, they may switch if the switching cost is low (Yang Z. &., 2004). Switching costs in the digital marketplace might include search and assessment costs, learning costs, brand relationship costs, uncertainty, and artificial limits designed by platforms to retain users (Ghazali, 2011). The strategic importance of switching costs is well recognized in industrial and economic theory, since they enable businesses to lock in clients and achieve a competitive advantage, particularly in marketplaces with homogeneous products (Klemperer, 1995). However, switching costs are not always advantageous; for example, procedural switching costs such as complexity or time strain may result in poor word-of-mouth and consumer displeasure, even if relational costs produce favorable results (Jones M. A., 2007). Furthermore, cultural characteristics influence how consumers perceive switching costs, with customers in collectivist cultures or low-income markets being more sensitive to such costs than those in individualistic or high-income markets (Pick, 2016). Researchers in the online and IT service sectors have created quantitative models to calculate switching costs based on platform dependency, customization levels, and user experience, highlighting their importance in user retention and system design (Chen P. Y., 2002; Whitten, 2006).

2.9 Perceived Value

Perceived value is a consumer's total opinion of the utility of a product or service based on what is received and what is provided (Chang T. Z., 1994). It involves a subjective evaluation that compares the benefits gained with the costs incurred, and this trade-off affects the perceived value of a product or service to the customer (McDougall, 2000). (Yang Z. P., 2004) says that perceived value has a big effect on how happy and loyal customers are, especially when the costs of switching are low or moderate. Researchers assert that perceived value is a complex construct encompassing functional, monetary, emotional, and social dimensions (Chuah S. H., 2016). The consumer not only receives essential services but also assesses price fairness, brand image, innovation, and relational quality (Edward M. G., 2010). When it comes to digital services like smartphones or social networking sites, perceived value includes things like how easy they are to use, how useful they are, and how much fun they are (Yen K. L., 2015). Additionally, perceived value acts as a bridge between the quality of a service and how a customer plans to act. For instance, when users get good service, they feel like they are getting more value, which makes them happier and less likely to switch (Liu C. T., 2011). Similarly, in highly competitive service marketplaces, companies can increase perceived value through marketing innovation, influencing customer loyalty (Chuah S. H., 2016). Interestingly, customer satisfaction affects perceived value, creating a feedback loop in which happy customers see more value in a service and are therefore less likely to switch (Hsu, 2014). This effect is stronger when it's easy or possible to switch, which is why perceived value is the most important psychological factor for keeping users (Lin C. N., 2017). Also, when service providers fail or don't do their jobs well, perceived value can drop quickly, which can make people switch (Zhang, 2007). Perceived value is an important idea for understanding why people make choices because it links how people feel about a service and their desire to switch to another one. Even loyal customers may think about their options and switch to something else that meets their needs if businesses don't always offer perceived value (Hussain, 2022).

2.10 Intention to Switch

According to (Asimakopoulos, 2014), a customer's intention to switch refers to their deliberate and conscious decision to move to a different platform, product, or service provider in the future. According to Sharma (2018), switching intention reflects a customer’s behavioral tendency, capturing both their dissatisfaction with current services and the perceived benefits of switching to alternatives. Such intentions often arise when consumers face declining satisfaction, reduced perceived value, or encounter more appealing market options (Zhang, 2007). Within digital environments and technologically advanced markets, switching intention is recognized as a multifaceted construct shaped by elements such as peer influence, trust, and system usability (Lin, 2017). Research further suggests that switching intention acts as a psychological precursor to actual switching behavior, making it an important indicator of potential customer attrition (D’Alessandro, 2015). For instance, in the context of information systems, users are more inclined to switch when they perceive a system as ineffective or lacking in utility (Yen, 2015). Additionally, both emotional and cognitive evaluations—such as perceived risk, satisfaction levels, and switching costs—play a role in shaping these intentions (Yang, 2004). Customers who consistently express a strong desire to switch, even if they delay action, are often considered less loyal to the service provider (Edward & M., 2011).

2.11 Correlation Between Ease of Use and Intention to Switch

Ease of use plays a critical role in shaping customers' decisions to switch between technologies, particularly when alternative systems are perceived as more intuitive and user-friendly (Kim, 2007). A strong relationship exists between ease of use and switching intention, as students are more inclined to adopt AI tools that demand less effort, streamline tasks, and deliver faster outcomes (Zhou, 2011). Prior research further indicates that users often abandon overly complex systems in favor of platforms that enhance usability while minimizing the learning curve (Venkatesh et al., 2000). This tendency is evident in today's AI landscape, where students frequently experiment with multiple platforms but gradually gravitate toward those offering the most seamless user experience (Lee, 2003). In our current study, where various AI tools are widely available, students have been observed rotating between platforms such as ChatGPT, Claude, and Google Gemini, frequently mentioning simplicity of use as a critical aspect. This switching tendency is consistent with the broader hypothesis that perceived ease of use greatly lowers the barriers to adopting alternative technology (Davis, 1989). Thus, the easier an AI tool is to use, the stronger the intention among students to switch to it, especially when contrasted to more sophisticated or labor-intensive alternatives (Venkatesh V. &., 2008).

H1: Ease of use significantly influences user intention to switch in AI

2.12 Correlation Between Social Influence and Intention to Switch

Social influence has a tremendous impact on users' behavioral intentions to switch from one platform or technology to another (Ajzen, 1991); (Venkatesh V. &., 2000). In (Zhou T. , Understanding users' switching between social media platforms: a PPM perspective, 2022) examination of social media platforms, social influence was discovered to directly boost users' propensity to switch by reinforcing dissatisfaction and perceived benefits of alternatives. (v. Wangenheim, 2004) have discovered that word-of-mouth, a type of social influence, strongly motivates customers to switch service providers, especially when the communicator is viewed as credible and similar. (Oh, 2020) found that, in smartphone environments, users' intents to switch are significantly impacted by peer and media influence, particularly when emotional reactions are present. In the present environment, with the advent of many AI platforms, students' intention to switch between different AI tools has shown a positive link with social impact as peer usage, recommendations, and debates progressively alter their view of tool effectiveness and usability. Furthermore, (Hu, 2019) discovered that contagious switching behavior spreads via social learning, in which people mimic switching actions from their social network. Overall, there is a persistent positive association between social influence and switching intentions across many technology areas, validating its theoretical and empirical significance (Cheung, 2010); (Chang I. C., 2014)**.**

H2: Social influence has significant impact on switching to AI

2.13 Correlation Between Attitude and Intention to Switch

According to (Ajzen, 1991), attitude is a person's overall assessment, whether favorable or unfavorable, of carrying out a particular behavior Research has shown that attitude is a significant predictor of users' intention to switch platforms, particularly within the realm of educational technologies and AI tools (Ma, 2024). When students hold a positive attitude toward a new AI-based learning tool—due to its advanced features, convenience, or effectiveness—they are more likely to transition from previously used tools (Milicevic, 2024). For instance, Ma (2024) conducted a cross-cultural study revealing that both Chinese and international students' favorable perceptions of AI strongly influenced their behavioral intention to adopt and engage with such technologies. The study reported a notable correlation between attitude and behavioral intention ($r = 0.45$–0.47), reinforcing the role of attitude as a key determinant in technology switching. Similarly, our current findings reflect this pattern: students who previously relied on a single AI tool are now gradually moving to alternatives with enhanced features, highlighting the substantial impact of attitude on switching behavior. Milicevic (2024) further demonstrated, through a structural modeling approach, that a positive attitude strongly predicts both the intention to use and the intention to switch AI technologies in educational contexts, especially when associated with perceived usefulness and ease of use. Collectively, these consistent results across educational settings underscore the critical role of attitude in shaping students' decisions to transition between AI tools when more advantageous options are available.

H3: Attitude significantly influences user intention to switch to AI.

2.14 Correlation Between Trust and Intention to Switch

Trust is a significant determinant influencing customers' choice to transition from one service or product provider to another (Mariska S. R., 2022). When customers lose faith in their current provider, they are more likely to look into other options, which makes them want to switch even more (Yen Y. X., 2010). Conversely, elevated trust levels generally diminish switching intentions by fostering loyalty and satisfaction

(Putra, 2019). Research consistently demonstrates that trust serves as a mediator between satisfaction and switching intention, enhancing customer commitment and reducing the likelihood of switching (Antón C. C., 2007). For instance, in the banking and service sectors, trust established through consistent positive interactions and effective communication creates a psychological impediment to switching (Han H. H., 2013). In this study, a decline in students' trust in AI tools is directly correlated with an increased intention to transition to alternative platforms perceived as more reliable or aligned with their expectations. Furthermore, trust modifies the link between switching costs and switching intentions. When trust is high, switching prices have a bigger impact on limiting switching intention because customers view the dangers of switching as greater (Carter, 2014). On the other hand, a lack of trust can overcome switching costs, encouraging consumers to switch even if the costs are high (Hauff, 2019).

H4: Trust plays a significant role in user intention to switch to AI.

2.16 Correlation Between Switching Benefit and Perceived value

Various consumer behavior models show a favorable correlation between switching benefit and perceived value. When consumers feel significant gains from switching, they tend to value the alternative option more, increasing their likelihood of switching (Kim H. W., 2010). Perceived value, in particular, serves as a cognitive assessment of the net gain a user anticipates—if the benefits of the new service outweigh the cost or difficulty of switching, the value perception increases (Msaed, 2017). According to studies conducted in the high-tech and mobile industries, when switching benefits such as feature upgrades, simplicity of use, or brand innovation are present, customers report higher perceived value of the new brand, demonstrating a direct and positive association. This association applies to both the hedonic (emotional/social) and utilitarian (functional) dimensions of value (Wong, 2019). In the case of Bangladeshi university students, many have switched between different AI tools due to the perceived values of advanced features, language support, or ease of learning, which has increased the perceived value of alternative platforms indicating a strong positive correlation between switching benefit and perceived value in determining switching behavior. In summary, the greater the perceived advantage of switching, the greater the value associated with the new service/product, resulting in stronger switching intentions (Lu T. T., 2011; Kim H. W., 2010).

H5: switching benefits positively influence perceived value to use AI.

2.17 Correlation Between Switching Cost and Perceived value

(Burnham T. A., 2003) define switching cost as the perceived economic, psychological, and procedural hurdles that users identify with transferring from one service or product to another. These switching costs frequently function as deterrents, inhibiting users from switching to alternative options, even when those alternatives may provide superior advantages (Jones M. A., 2000). Perceived value, on the other hand, is described as the customer's entire assessment of a product's utility based on what is received against what is given, which includes performance, price, time, and effort (Zeithaml, 1988; Yang Z. P., 2004). When consumers perceive high value, they are more likely to acquire pleasure and loyalty to the service or tool, which can lower their risk of switching (Chang H. H., 2009). However, when switching costs are high, even if perceived value decreases marginally, users may continue to use the current service due to the difficulty of change (Lee J. L., 2001). Surprisingly, perceived value might increase the perception of switching costs—particularly when customers are emotionally or functionally attached to a high-value service (Sujatha, 2013)Students frequently question whether the perceived benefits of alternative tools in contemporary digital environments like AI-powered educational tools justify the effort to switch, particularly when switching costs are low (Kim M. K., 2004). Higher perceived value (e.g., better performance, user experience, or features) is driving Bangladeshi university students to switch between AI tools more frequently. which low switching costs facilitate and increase (Yang Z. &., 2004; Sujatha, 2013). Therefore, the relationship between perceived value and switching costs is reciprocal: switching costs affect how students assess value during transitions, while perceived value influences willingness to pay switching costs. (Burnham T. A., 2003; Lee J. L., 2001).

H6: Switching cost negatively affects Perceived value to use AI.

2.18 Correlation Perceived value and Intention to Switch

Perceived value is one of the most important determinants of customers' desire to switch services or goods, reflecting the user's perceived balance of advantages over costs (Zhang, 2007). When clients believe that an alternative service provides more value than their present supplier, they are more likely to move (Lu T. T., 2011). In competitive markets, perceived value serves as a psychological trigger, directly influencing behavioral intentions, especially when switching barriers are low (Lin C. N., 2017). There is a strong correlation between perceived value and switching intention, as evidenced by the fact that many Bangladeshi university students move between AI tools because they believe the alternatives offer greater educational and practical value. Research indicates that customers are always comparing service outcomes and are more likely to switch to a different supplier if they perceive the value to be higher (Hsu, 2014). In digital and technology-based services, where users are more cognizant of their options and can swiftly assess functional, monetary, or emotional value differences, this association is particularly noteworthy (Yen K. L., 2015). Regardless of prior loyalty, clients are more likely to switch providers if they believe the new provider will offer them greater functional and financial value (Chuah S. H., 2016). Furthermore, perceived value influences switching not just directly but also indirectly through satisfaction and trust, shaping the overall desire to switch (Yang Z. P., 2004). Customers may stay with a provider despite minor discontent, but if they perceive better value elsewhere, they may switch (McDougall, 2000). (Hussain, 2022) found that in price-sensitive businesses such as electricity services, perceived relative value has a considerable influence on customer switching behavior, particularly when alternatives offer better price-performance ratios.

H7: Perceived value significantly influences perceived value to use AI.

2.19 Hypothesis and Structured Model

2.19.1 List of all Hypothesis

Table 2.1: List of Hypothesis Description

SL NO	Hypothesis Description
H1	Ease of use significantly influences user intention to switch in AI
H2	Social influence has significant impact on switching to AI
H3	Attitude significantly influences user intention to switch to AI.
H4	Trust plays a significant role in user intention to switch to AI.
H5	Switching benefits positively influence perceived value to use AI.
H6	Switching cost negatively affects Perceived value to use AI.
H7	Perceived value significantly influences perceived value to use AI.

2.19.2 Structured Model

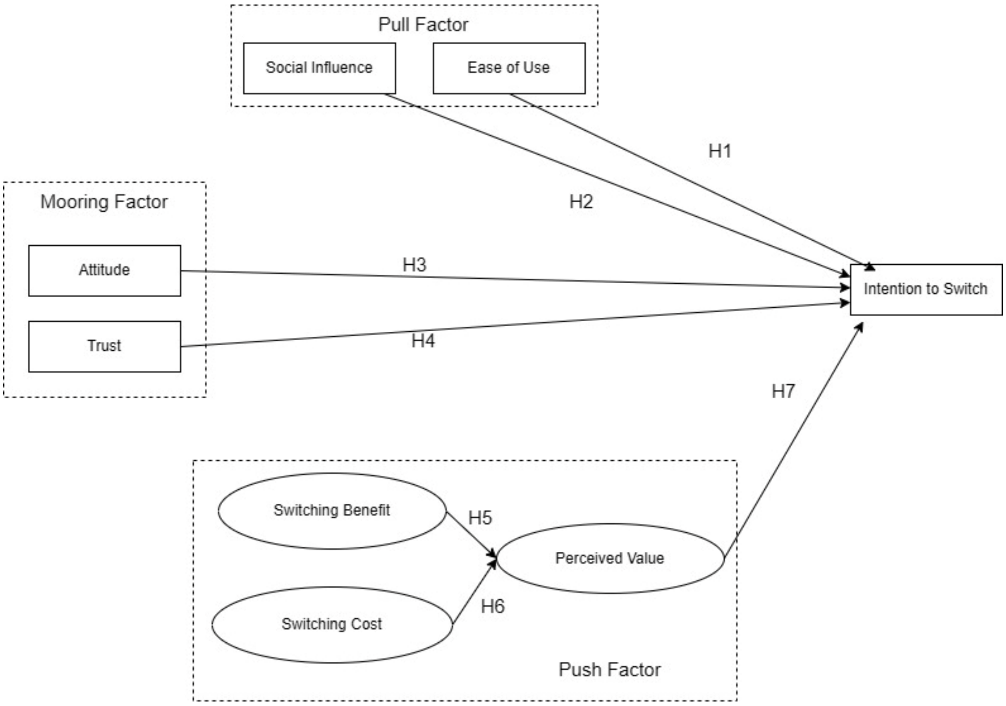

Fig 2.1: Proposed Thesis Model

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Quantitative Research

"Quantitative research" is defined differently by many academics and educators. Here are several examples: Quantitative research involves numerically representing and manipulating observations to describe and explain events. It is utilized in various natural and social sciences, such as physics, biology, psychology, sociology, and geology. (Cohen, 1980) defines quantitative research as social research using empirical methods and assertions. According to the author, an empirical assertion describes what "is" in the "real world" rather than what "ought" to be the case. In quantitative research, empirical statements are often expressed numerically. Additionally, empirical evaluations are used. Empirical evaluations assess whether a program or policy meets a specific criterion or norm. Quantitative research is very adaptable due to its ability to explore virtually any phenomenon. However, not every phenomenon is best explored using quantitative methods. methods. Quantitative approaches offer both advantages and disadvantages. This suggests that qualitative methods are more appropriate for studying certain phenomena. In summary, quantitative research seeks to measure social reality. Quantitative research involves identifying quantities and establishing research through numerical methods. Quantitative researchers rely on objective guidelines for data gathering and analysis.

Different Types of Quantitative Research

There are different sorts of quantitative research. For example, it can be classed as survey, correlational, experimental, or causal-comparative research. Each variety has its own distinguishing qualities.

3.2 Research Process

This research followed a standard scientific research process. The research process involves seven stages: problem, hypothesis, design, measurement, data collecting, analysis, and generalization. According to (Fornell C. &., 1981), each stage has an impact on theory and vice versa. The study approach began with a review of the literature to identify gaps and establish research questions. Chapter Two included a detailed review of relevant literature, while Chapter One outlined the study's research questions. The review of literature resulted in the identification of relevant theories, which served as a foundation for establishing the theoretical framework and hypotheses for this study. The third chapter covers the theoretical framework and theoretically justified hypotheses for this study. The next step was to establish the best research design to use in this study. First, the researcher required to determine the appropriate study paradigm, as explained in the previous section of this chapter. After deciding on the study paradigm, the suitable research design was implemented. During the measuring phase, the survey questionnaire was carefully designed. During the final phase, a pilot study was conducted to assess the survey questionnaire's reliability and face validity. The results of the preceding phase were used to make necessary changes to the survey questionnaires. After the survey questionnaire had been reviewed and approved, the instrument was utilized to Collect data from the samples. The data were then evaluated in two parts. Preliminary data analysis was conducted to cleanse the data and gain a comprehensive understanding of the respondents. In the second Phase, structural equation modeling was used. Chapter 5 provides an explanation for data analysis. The final stage entailed interpreting findings and discussing their implications. Chapter Six goes over all of these difficulties. To provide a thorough explanation and discussion of the findings, researchers should consult relevant theories and literature.

3.3 The Survey Methods

Gathering information from respondents about their moral disengagement tendencies, personality traits, leadership styles, the ethical climate of their companies, and examples of deviant workplace behavior necessitates dealing with sensitive topics. The survey method is an effective and systematic means to collect sensitive data because it allows the researcher to obtain standardized responses from a defined population while maintaining comparability among participants (Schwarz, 1998). This method provides for efficient data collecting from large samples, making it ideal for studies aimed at identifying patterns and correlations between many variables. Surveys are especially useful in behavioral research because they may capture respondents' attitudes, beliefs, and self-reported behaviors in a systematic and quantitative format. The versatility of survey design allows researchers to cover a wide range of constructs inside a single instrument, allowing hypothesis testing and statistical analysis (Schwarz, 1998). Furthermore, standardized questions contribute to measurement consistency, which is necessary for deriving meaningful conclusions and generalizing findings to a larger population. However, surveys have some downsides, such as nonresponse bias, measurement error, and the inability to capture the full range of participants' experiences. To address these problems, our study used rigorous questionnaire design techniques, verified measurement scales, and pre-testing to assure clarity and reliability. Such approaches, as advocated by (Schwarz, 1998), serve to mitigate frequent survey method constraints while also improving data accuracy.

3.4 Survey Questionnaire Adaption

Variable	Author
Attitude	(Ajzen, 1991)
Ease of Use	(Kim H. W., 2007)
Intention to Switch	(Ajzen, 1991)

Perceived Value	(Lu T. T., 2011)
Social Influence	(v. Wangenheim, 2004)
Switching Benefit	(Kim H. W., 2010).
Switching Cost	(Chang H. H., 2009)
Trust	(Mariska S. R., 2022)

Table-3.1: Questionnaire Adaption

3.5 Questioner

A questionnaire is defined as "a reformulated written set of questions to which respondents provide their answers, typically within narrowly defined response options" (Liu Z. &., 2018). In this study, questionnaires served as the primary data gathering instrument. This method is widely recognized as a successful means to gain information from large sample groups (Matsumori, 2021), and it is regarded one of the most commonly used data collection methods (Baker, 2003). The questionnaire was broken into two major portions. The first segment asked demographic questions, whereas the following sections comprised items developed specifically to measure the constructs under inquiry.

Section A

In this section, the demographic information of participant is included.

Section B

This section includes 24 questions asking respondents to prove our hypothesis.

Participant had to answer by marking based on the scale.

Strongly Disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

Table-3.2: 7 Point Likert Scale

3.6 Sample Size

To acquire empirical data for the research model, we created a survey to test our hypothesis. Structured questionnaires were used to survey the samples. A priori analysis can effectively manage statistical power before a study is done (Kang, 2021). By utilizing the program, G*Power 3 was used with medium effect size, probability of Type I error $\alpha = 0.05$, probability of Type II error $\beta = 0.05$ $(1-\beta) = .95$, and 7 predictors (IQ, SQ, and SAT antecedents). The estimated sample size was 180, with 95% power. We distributed 350 questionnaires and obtained 320 responses, representing an 91.43% response rate.

3.7 Data Collection Procedure

The major approach used to collect data for this study was a self-administered questionnaire. A self-administered questionnaire is described as "a data collection technique in which respondents read the survey questions and record their answers without the presence of a trained interviewer" (Ariyo, 1998). This method was chosen because it encourages more honest responses, as respondents are less impacted by social desirability bias than interviewer-administered surveys (Kristjansson, 2013). The questionnaire utilized in this study was carefully designed by synthesizing pertinent questions from various current research publications, ensuring that the material was appropriate and thorough for the context of this investigation. After completing the questionnaire, data were collected using a drop-off and collect approach. A study representative delivered the questionnaires directly to respondents at their location, and the completed surveys were collected later (Ariyo, 1998). This strategy allowed respondents to complete the questionnaire at their own pace and leisure, giving them time to carefully evaluate each question and seek more information as needed (Ariyo, 1998). Furthermore, the presence of a research representative to hand-deliver the questionnaire assisted in clarifying any questions respondents had and enhanced their enthusiasm to participate through direct engagement (Ariyo, 1998).

3.8 Demographic Information

Table 3.3 highlights the demographic characteristics of the 350 respondents, all of whom were university students or individuals with ties to higher education in Bangladesh. The bulk of participants were men (84.9%, n = 297), with women accounting for 15.1% (n = 53). In terms of age distribution, most respondents (94.9%, n = 332) were between 18 and 22 years old, with lower numbers of 23-27 (1.7%, n = 6) and 28-32 (3.4%, n = 12). In terms of educational background, the majority (93.4%, n = 327) were at the HSC level, followed by graduates (5.1%, n = 18), those with SSC qualifications (0.6%, n = 2), and a small number (0.9%, n = 3) who indicated schooling above the postgraduate level. Almost all respondents (98.6%, n = 345) reported using AI, with ChatGPT being the most popular tool (99.4%, n = 346), followed by DeepSeek (65.5%, n = 228), Gemini (57.8%, n = 201), and other AI platforms (88.2%, n = 307), with only one respondent (0.3%) mentioning using Llama. In terms of usage frequency, everyday AI use was most common (96.8%, n = 337), with a tiny minority using AI tools monthly (2%, n = 7) or seldom (1.1%, n = 4). These findings reveal a high level of AI engagement among Bangladeshi university students, making them an appropriate population to study switching habits between AI platforms.

Table 3.3: Demographics

DEMOGRAPHIC INFORMATION	N	%
Gender		
Male	297	84.9%
Female	53	15.1%
Age Range		
18 - 22	332	94.9%
23 - 27	6	1.7%

28 - 32	12	3.4%
Above	0	0%
Education		
SSC	2	0.6%
HSC	327	93.4%
Graduate	18	5.1%
Postgraduate	0	0%
Above	3	0.9%
Do you use any AI?		
Yes	345	98.6%
No	5	1.4%
If yes, which AI(s) do you use?		
ChatGPT	346	99.4%
DeepSeek	228	65.5%
Gemini	201	57.8%
Llama	1	0.3%
Others	307	88.2%
How long have you been using this AI?		
Daily	337	96.8%
Weekly	7	2%
Monthly	0	0%
Occasionally	4	1.1%

To evaluate out model we measured Average variance extracted (AVE), Composite Reliability (CR), Discriminate validity and Effect Size.

AVE: Average Variance Extracted (dos Santos, 2023) suggested Extracted as a measure of shared or common variation in a Latent Variable (LV), capturing the amount of variance compared to measurement error (Haji-Othman, 2022). AVE measures the error-free variance of a set of elements. According to (dos Santos, 2023), convergent LVs should include measures with more than 50% explained or common variance in the factor analytic sense (less than 50% error variance; see also (Haji-Othman, 2022)). (dos Santos, 2023) define λ i as the loading of x i on X, Var as the measurement error, and Σ as the sum.

CR: Composite reliability is often calculated using structural equation modeling. Latent Variable (LV) reliability assesses the correspondence between items and their LV, as well as the correlation between an LV and its items. "Correlations less than 0.7" do not consider measurement error. Square the total of all factor loadings (referred to as the SSI). The sum of each indicator's error variances (SEV).

$$CR = SSI/ (SSI+SEV)$$

Discriminate Validity: The diagonal indicates the square root of Average Variance Extracted (AVE), whereas the remaining entries show squared correlations. (dos Santos, 2023) define quality criteria as the square root of AVE being greater than the associated construct correlation, indicating that a model concept is actually distinct from others.

F2: F 2 is a measure used to determine the effect of an independent variable. (Cohen, 1980) defines criteria of 0.02, 0.15, and 0.35 for measuring tiny, medium, and large impacts.

CHAPTER 4: RESULT AND DISCUSSION

4.1 Data analysis technique

The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. PLS-SEM is a popular variance-based structural equation modeling technique that works well for exploratory research and complex models with numerous constructs (Sobaih, 2022). This technique enables for the simultaneous assessment of the measurement model (validity and reliability of constructs) and the structural model (relationships between constructs), resulting in robust estimates even with small sample numbers (Pratiwi, 2022). SmartPLS was chosen due to its user-friendly interface and high skills in predicting latent variable correlations, making it perfect for evaluating data from self-administered questionnaires. The study was conducted in two steps: measurement model evaluation to establish construct reliability and validity, and structural model testing to analyze predicted correlations among variables (Sobaih, 2022).

4.2 Measurement Model

Researchers should test the outer model after creating the research model, according to (dos Santos, 2023).To evaluate the outer model, we assessed average variance extracted (AVE), composite reliability (CR), and discriminate validity.

Table 4.1: AVE

	AVE
Attitude	0.702
Ease of Use	0.942
Intention to Switch	0.799
Perceived Value	0.819
Social Influence	0.669
Switching Benefit	0.746
Switching Cost	0.803
Trust	0.772

Table 4.2: Composite Reliability

	CR
Attitude	0.870
Ease of Use	0.914
Intention to Switch	0.922
Perceived Value	0.900
Social Influence	0.890
Switching Benefit	0.921
Switching Cost	0.923
Trust	0.910

Table 4.3: Latent Variable Correlations (Discriminant Validity)

	AT	EU	SWI	PVL	SI	SWB	SWC	TR
Attitude	0.838							
Ease of Use	0.818	0.918						
Intention to Switch	0.338	0.533	0.894					
Perceived Value	0.710	0.724	0.668	0.905				
Social Influence	0.533	0.616	0.708	0.753	0.818			
Switching Benefit	0.850	0.943	0.468	0.667	0.630	0.864		
Switching Cost	0.331	0.539	0.726	0.536	0.811	0.521	0.896	
Trust	0.474	0.645	0.775	0.756	0.802	0.529	0.727	0.879

According to (dos Santos, 2023), our variables meet the quality criterion of AVE larger than 0.5, indicating that at least 50% of items explain the construct, and composite reliability greater than 0.7. Table 3 demonstrates that the square root of AVE is bigger than the related construct correlation, indicating that our construct is unique from others (dos Santos, 2023).

4.3 Structural Model

Among all factors, Trust was found to have the largest direct effect on Intention to Switch, with a path coefficient of 0.401 (T = 2.822, P = 0.003), demonstrating that trust is a major and positive motivator for students to switch AI tools. This is consistent with previous research, which has emphasized the importance of user trust in digital platform adoption and behavioral change (Mariska S. R., 2022). A positive attitude toward the current AI tool may reduce the likelihood of switching, aligning with prior studies that highlight attitude as a stabilizing factor in technology use (Chen Y. P., 2022). Perceived value ($\beta = 0.243$, $T = 2.042$, $P = 0.021$) and social influence ($\beta = 0.223$, $T = 2.083$, $P = 0.019$) had a big effect on switching intention. These findings indicate that students are more inclined to switch when they recognize greater value in alternative tools or when peers and influencers advocate for such transitions, thereby corroborating previous research on technology switching behaviors (Hsu, 2014). Ease of Use had a significant but lesser effect ($\beta = 0.157$, $T = 1.694$, $P = 0.046$), indicating that the simplicity and user-friendliness of new AI tools can affect switching behavior, but may not be the main reason. This aligns with the Technology Acceptance Model (TAM) and its focus on perceived ease of use (Davis, 1989). In the model, Switching Benefit had a big and important effect on Perceived Value ($\beta = 0.484$, $T = 2.674$, $P = 0.004$). This shows that students get more out of new AI tools and think they are more valuable. Students think that other tools are more valuable when switching costs are low (Liu A. H., 2006; Yang Z. &., 2004). In general, these data back up the research model. Trust, perceived value, social influence, and switching benefit are the most important factors that affect Bangladeshi university students' decisions to switch AI tools. P-values lower than 0.05 (Andrade, 2019) indicate that each path is significant, thereby validating the statistical reliability of the data. These results are helpful for AI developers and teachers who want to get more people to use their products and keep them by focusing on usability, building trust, and encouraging peer-driven adoption.

Table 4.4: Breaks down the significance of each path

	Original Sample (O)	T Statistics (|O/STERR|)	
Attitude -> Intention to Switch	-0.246	2.346	supported
Ease of Use -> Intention to Switch	0.157	1.694	supported
Perceived value -> Intention to Switch	0.243	2.042	supported
Social Influence -> Intention to Switch	0.223	2.083	supported
Switching Benefit -> Perceived value	0.484	2.674	supported
Switching Cost -> Perceived value	0.258	1.707	supported
Trust -> Intention to Switch	0.401	2.822	supported

The final validation of our research model utilizing survey data is presented in the figure.

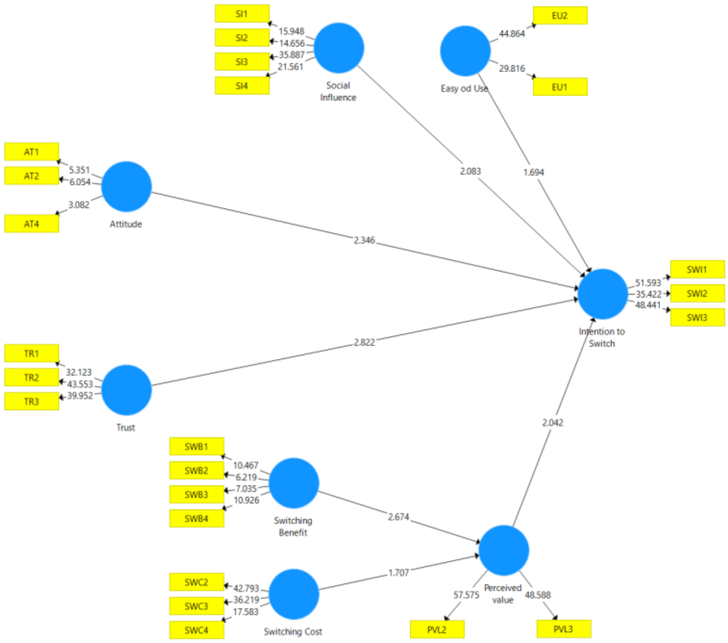

Fig 4.1: Tested Model with result

4.4 Discussion

The results of the current research indicate that the observed complexity in the interaction between perceived value, social influence, trust, switching benefits, and switching costs are the reasons that motivate the Bangladeshi university students to regularly change the tools used in AI. The concept of perceived value was found to be one of the strongest predictors of switching intentions, where students were more likely to switch to alternative AI platforms when the students had a perceived value of the tool as having better features, performance or better learning results (Yang and Z., 2004; Liu, 2006). The findings are in line with the previous research on the importance of value perceptions in determining technology adoption and replacement decisions. The social influence was also a major factor in the switching behavior. It is found that students were more likely to switch with the recommendation or endorsement of other AI tools by the teacher, peers or classmates and this conformed to the Theory of Planned Behavior which emphasized the effects of subjective norms when it comes to behavior intentions (Venkatesh et al., 2003). This implies that as powerful classmates use or promote the use of particular AI tools, other learners are likely to do the same. Another factor that was found critical was trust. Students also tended to engage with AI technologies that they found to be credible, open, and safe, and violations of trust, including false results, privacy, inconsistent performance, etc., encouraged them to seek an alternative (Mariska, 2022). The high rate of AI technology development as well as the regular additions of new functions in Bangladeshi higher education also serve to support the significance of trust and perceived advantages. Switching costs, such as time, effort, and learning to operate a new AI tool, may, however, act as obstacles. The availability of lower switching costs helps in faster adoption of new tools and the perceived costs make changes unnecessary (Burnham, 2003). It means that the students will probably keep using their existing AI tool until they feel that the advantages of switching it surpass the disadvantages. On the whole, these results indicate that switching between AI tools among the students of the Bangladeshi university is a dynamic process, yet it is influenced by both functional and psychological aspects. The hurried technology world prompts the students to constantly test the new tools with regard to reliability, acceptance by peers, and its academic appropriateness. Shedding light on the significance of improving the perceived value, building trust, and using the social influence to encourage long-term adoption and reduce avoidable switching, these insights have implications that can be applied by AI developers and educational policymakers.

CHAPTER 5 CONCLUSIONS & RECOMMENDATIONS

5.1 Implication

The present study is enriching both in terms of theoretical knowledge and practical uses in terms of the switching behavior of the Bangladeshi university students across various AI tools. To begin with, the greater influence of social influence on switching intentions highlights the importance of social networks and peer recommendations in changing technology and transitioning to it (Ajzen, 1991; Venkatesh et al., 2000). This can be exploited by educational institutions and providers of AI services to create an environment, which makes the students talk and suggest using AI tools and, therefore, ensure further use. Second, the factor of trust became one of the key ones, and the switching intentions of the students are heavily influenced by their belief in the reliability and the safety of the AI technologies (Mariska, 2022). The given finding highlights the importance of working on open and safe system design as a way of building user trust and mitigating switching behavior by AI developers. Besides, the attitudes of students toward the AI tools and their perceived ease of use are significant predictors of adoption behavior, especially when the technology is more user-friendly and more in line with the needs of the latter (Venkatesh, 2003). It is therefore vital to keep on improving user interface and overall experience, which will enable retention. More so, the more students feel that they have an added value or benefit in different AI platforms, the more they are likely to experiment them. Nevertheless, switching costs (in terms of time, effort and educational needs) may serve as obstacles to change (Burnham, 2003; Kim, 2010; McDougall, 2000). Providers of services can enhance retention by advancing the perceived value of their products and reducing the switching costs. Lastly, the research findings provide useful implications to educators and policymakers in Bangladesh who are interested in applying AI in schools. Addressing the categories of social influence, trust, usability, perceived value, and switching costs, the stakeholders can contribute to the implementation of AI solutions that will fulfill the needs of students without unnecessary switching.

5.2 Research limitations and future direction

The research provides valuable information regarding the switching pattern of the Bangladeshi university students when using various AI tools; nevertheless, a number of limitations should be considered. Firstly, the study failed to investigate the possible impact of Electronic Word-of-Mouth (e-WOM) or habitual behavior on switching intentions of the students. The two factors have been identified to be important predictors of technology adoption and further use in previous studies and their absence can decrease the breadth of the results. Moreover, the research was mostly based on self-reported data gathered by students in a small number of universities in Bangladesh, which can also restrain the ability to generalize the findings to other groups and settings. The variables to be incorporated in future study are e-WOM and habitual behavior, as it will help understand how they influence AI tool switching better. Longitudinal studies might also be used to aid in capturing temporal dynamics of switching intentions and behaviors. Also, the external validity and applicability of the results should be improved by including students representing more diverse universities and academic backgrounds. Overcoming these constraints in the future, the studies will be able to offer a more detailed view of the multifaceted nature of factors which drive the use and switching pattern of the AI tool in students.

5.3 Conclusion

This study explored the switching behavior of Bangladeshi university students across various AI tools, focusing on key determinants such as social influence, trust, attitude, ease of use, perceived value, switching benefits, switching costs, and switching intention. The findings reveal that social influence and trust exert a particularly strong effect on students' decisions to switch between AI platforms, while ease of use and perceived value also play important roles in guiding these choices. Additionally, the perceived advantages of switching encourage students to explore alternative tools, whereas switching costs may act as barriers to change. These insights offer a clearer understanding of the interaction between Bangladeshi students and AI technologies and provide practical guidance for AI developers, educators, and policymakers seeking to enhance user satisfaction and engagement. By taking these factors into account, stakeholders can design AI tools that better align with students' preferences and requirements in the rapidly evolving educational AI landscape. Future research should expand on this study by incorporating additional variables not considered here, such as electronic word-of-mouth (e-WOM) and habitual behaviors, which may further clarify the determinants of switching intentions. Overall, the study establishes a solid foundation for supporting the effective adoption and sustained use of AI technologies among university students in Bangladesh.

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