



Factors Influencing Switching Intentions of AI Tools in Library Settings: A Push-Pull Mooring Theory Approach

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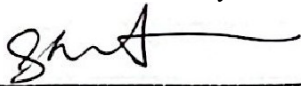
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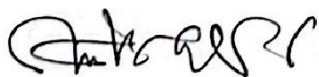
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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Daffodil International University or any other institution.

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ABSTRACT

This work seeks to explore how the switching intentions of traditional human librarian services to AI-based chatbots depend on factors among students. Research is directed by the Push-Pull-Mooring (PPM) theory, and its aims were to find out the key influencing factors, discuss the validity of the PPM theory, and to examine the relationships between variables. The study design was a cross-sectional survey that included 181 university learners. A hybrid data analysis approach that incorporates the Partial Least Squares Structural Equation Modelling (PLS-SEM) and Artificial Neural Network (ANN) was used. The results confirm that the push factors (dissatisfaction with the existing services) and pull factors (perceived responsiveness of AI chatbots) have a strong and positive impact on switching intentions. AI resistance was also determined to be augmented by the mooring effects of sunk cost and loss aversion. The research had two new and conflicting observations: the positive past AI experience was discovered to elevate AI resistance, and AI resistance was discovered to enhance switching intention. Its model showed a good explanatory power with 59.4 percent and 54.3 percent of variance in AI resistance and switching intention respectively. These findings have provided a delicate insight into the behaviour of the users and have given significant practical implications to the library administrators.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
PLS-SEM	Partial Least Squares Structural Equation Modeling
AVE	Average Variance Extracted
CR	Composite Reliability
PPM	Push-Pull-Mooring
RMSE	Root Mean Square Error
SEM	Structural Equation Modeling
SPSS	Statistical Package for the Social Sciences

CHAPTER 1

INTRODUCTION

1.1 Overview

The increasing needs of Artificial Intelligence (AI) across different industries have contributed to a radical change in service provision and library environments are not an exception. The study is aimed at exploring the factors that determine switching intent of the users towards traditional and human mediation of the library services to algorithm-enabled chatbots. Although the integration of AI can potentially help such aspects as uninterrupted accessibility and immediate help, a great number of users are not ready to make this transition to a complete use of AI. This paper seeks to give an in-depth insight of this behavior change using the theory of migration commonly known as Push-Pull-Mooring (PPM) theory which is an effective tool to explain such migration behavior applied in the case of library services. The paper will help in understanding user-technology interactions within the academic set up by establishing the important triggers, benefits and obstacles to such a change.

1.2 Background

Services in different sectors have changed due to the high uptake of Artificial Intelligence (AI) and chatbots. Libraries, specifically, are investigating the implementation of AI in their work to give the user experience as much support as though it is working around the clock and providing effective information search results. Nonetheless, this technological change is a challenge since many of the users are reluctant to transition to the new form of system interaction with AI-powered conversational agents and leave behind the personal interaction with human librarians. This reluctance in many cases is determined by a mixture of psychological and behavioural issues and practices, including, but not confined to, trust, habit, and perceived risk. This knowledge about such underlying motifs is vital to the adoption and marketing of AI-driven services by library administrators and technologists in order to provide an easy transition of those who will be using the service.

1.3 Problem Statement

The increasing applications of AI based-chatbots in the management of library services is a major trend, but it comes with a major issue; most of the users would remain reluctant to use it instead of ordinary librarians. As long as the Push-Pull-Mooring (PPM) theory is an effective framework to explain the occurrence of migration, it does not dominate over the issue of AI adoption in libraries since the theory does not bring in the extent of adoption. Such absence of research implies that the concrete behavioral and psychological conditions determining the choice of a user to switch to another are still not explored. The big question that needs to be answered is what influences this switching decision through stimulating (push), problems (mooring) and benefits (pull).

1.4 Research Gaps and Research Questions:

This section will explicitly list the gaps your research addresses and the questions it aims to answer.

1.4.1 Research Gaps:

- There is a paucity of literature that has used the Push-Pull-Mooring (PPM) theory to comprehend behaviour of switching users of AI-based library services.
- Not many studies focus on the mooring effects (ex. trust problems, habit forming) that serve as hindrance to library service adoption of AI.
- The psychological and behavioural factors by which a user will shift between traditional librarians and AI chatbots have not been researched much.
- Previous studies lack empirical evidence on the interaction of push (dissatisfaction), pull (AI benefits) and mooring (barriers) factors in determining the switching decision of a user.

1.4.2 Research Questions:

AI-driven conversational agents bring a lot of convenience and proactive support that sometimes even outperform human librarians, at least in certain aspects, while dealing with repetitive or simple queries. Hence, many libraries are currently shifting away from dependence on human librarians to the inclusion of AI-driven chatbots within their service frameworks (Leung and Yan Chan, 2020). Despite this change, information about library users' perception of services offered by human librarians in comparison with those from AI driven chat assistants is still very limited (Prentice et al., 2020). This paper will examine relevant factors determined by library users' behavioural change from reliance on human librarians to adopting AI-based CAs. Thus, the initial research question:

Research Question 1: What are the factors that determine library users to switch behavioural patterns between human librarians and AI based conversational agents?

The concept of migration that underlies the PPM framework, which was initially published by Moon (1995) could be applied to the process of moving towards using human librarians to AI-powered CAs in libraries. Boyle et al. (1998) also argue that the PPM framework outlines three major factors that determine user intent to switch; push, pull, and anchoring. This paradigm has been adapted to many fields of study, such as consumer switching behaviour, involving the switching between online and offline platforms and towards new and old technology (Chen and Keng, 2019). It has been applied to the retail industry (Singh and Rosengren, 2020), marketing industry (Tang and Chen, 2020) and electronic commerce (Frasquet and Miquel-Romero, 2021). The PPM model might be particularly applicable to researching the switching behaviour of library users between the experience with librarians and AI-powered chatbots.

In this way, the second research question will be the following:

Research Question 2: How do the variables of anchoring, push, and pull affect the decisions of library users whether to switch to the use of a human librarian in their library or switch to the use of a conversational artificial intelligence-driven bot? In this library situation, the push effects refer to aspects that prompt users to abandon the old services of librarians based on the perceived limitations of such services by users, such

as low availability, low flexibility, and no real-time feedback. These are negative aspects that compel users to go to other alternatives. The positive forces which entice users to AI-based CAs are the pull factors, which include 24 /7 support, anywhere access, and answering questions immediately. Mooring effects: These are situational or individual influences that either encourage or discourage switching behaviour among the users. These are the frequency of the library service requirement of customers, their technological competence, and the specificity of their service requirement. Such results will have high significance to library administrators as well as practitioners in the adoption of AI technologies which will assist them to build relationships with users, improve service experiences and ultimately lead to the happiness of people.

1.5 Research Objectives:

The research objectives are clear statements of what your study aims to achieve.

- **RO1:** To determine the reasons behind the behavioural change of library users switching human-mediated services to AI-based conversational entrenched agent, technological reasons, as well as reasons on the aspect of providing services themselves.
- **RO2:** To investigate how the Push-Pull-Mooring (PPM) theory can be utilized to explain the phenomenon in which library users, when faced with the expanding options to converse with human librarians, switch to conversing with AI-based conversational agents.
- **RO3:** In order to establish the factors that have the greatest effects on switching intentions using a PLS-ANN integrated model that enables an in-depth analysis with predictive power.

The goals of the research will fill in the identified gaps by finding towards the particular drivers and the basis on which users are discouraged by the traditional library services and shift towards the use of the AI-based tools as well as analyse the opposite pull; the mooring effects; which generate the resistance to change. The paper shall then use the Push-Pull-Mooring concept to formulate this knowledge. Lastly, through the application of a hybrid PLS-ANN model, the study aims to give a complete analysis in a way that as well as confirming relationships, it can also lend predictive capability on a subset of

explanatory variables that may be of the sole value in terms of influencing a decision to switch choice.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature Overview:

The Push-Pull-Mooring (PPM) frame is an organizational theory of understanding users switching behaviour across different areas. This model elucidates that the choice of a user to shift service provider by a user depends on the three primary forces, these being push factors that creates dissatisfaction with the current service; pull factors that entices the user to a different one; and mooring factors that either is a hindrance or enabler of the transition.

PPM framework has been used in the past to look at various scenarios such as switching between ERPs systems, mobile applications, digital payment services, and even between traditional classrooms and smart classrooms. Most recent studies have expanded this model into scoping user migration between established services and generative AI services such as search engines and social Q&A communities to generative AI services. Information overload, fatigue in the community, and perceived inefficiency, have been found as push factors in these studies. The perceived attractiveness of alternatives, i.e. the interactivity, content quality and accuracy of AI give rise to a lot of pull factors. Switching costs, social influence, inertia and technical self-efficacy have been identified as Mooring factors that may prohibit or enable a switch.

The methodologies elaborated in these research works mostly use Structural Equation modelling (SEM) and its variations like PLS-SEM to assess quantitative information as a result of the survey research. Other authors have made use of a mixed-method approach by adopting a combination of SEM and Fuzzy-Set Qualitative Comparative Analysis (fsQCA) to delve into the dynamisms of interactive and composite factors in bringing about switching behaviour. The research article specifically addressing chatbots in healthcare even incorporated the theory of status quo bias as part of the PPM framework to develop arguments deciphering how switching intentions are negatively impacted by

AI resistance bias, and how the former bias is mediated by such variables as relationships with doctors and previous experiences with AI.

2.2 Previous Literature Review

McKenna et al. [1] utilized the PPM framework herein for an analysis of switching behaviors among smartphone messaging services via a qualitative method. Under a laddering interview method, the message context, message content, and the services' features were the key motivators for user switching behaviour identified by the study. These outcomes assist in building more depth into the determinants for customer decisions within such a fast-evolving marketplace.

Kusumah et al. [2] explored the Push-Pull-Mooring model is employed for the analysis of drivers of movement into the OVO mobile payment system. In a multiple regression analysis of 400 surveys, the results are that push and pull forces both provide significant support for intentions to switch, but the mooring force provides significant deterrence. The implications for the development of better services and user retention for the mobile payments sector are listed.

T. Zhou et al. [3] focused on assessing the user switching intention in the generative AI platforms based on the push-pull-mooring (PPM) framework. The push factors are: information hallucination, privacy risk and dissatisfaction. Internationality, anthropomorphism, personalization and user experience are perceived as pull factors. The mooring factor is switching costs. The research confirms the hypotheses based on the structural equation modelling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA) which indicate that dissatisfaction is a fundamental prerequisite of evoking switching intention. This paper discusses the issue of losing users and competitive edge within the generative AI market.

S. Liang et al. [4] looked at the determinants of user application switching behaviour when performing mobile searches using the push-pull-mooring (PPM) model. The results of the study of 374 respondents, calculated based on a structural equation model, provide important perspectives. The complexity of search tasks is a push factor that has a positive impact on switching intention, and the attractiveness of other products and follow-up

activities are pull factors. Further, inertia is a stabilizing force of a push-pull factor, which promotes relationships between push and pull factors and user switching intentions. The results provide useful guidelines to the developers of applications to enhance user retention and search experiences.

T. Zhou et al. [5] used the push-pull-mooring (PPM) model to examine user switching intention between search engines and generative AI as information seekers. Results suggest that dissatisfaction is the result of low information-task fit and information overload (push factors) and the quality of AI generated content (AIGC) and perceived interactivity (pull factors). The determinants associated with switching intention are dissatisfaction, perceived value and social influence. The study offers practical recommendations to the providers of search services to help them increase user retention and sustainable development.

H. Jo et al. [6] examined the predictors of the intention to switch as an ERP user based on the push-pull-mooring (PPM) model. According to the results of the data of 236 users, which are analysed using structural equation modelling, it can be concluded that the quality of systems, quality of information and support of top management affect the intention to switch based on satisfaction. In particular, the effect that user satisfaction influences switching intention is negative, whereas alternative attractiveness influences the switching intention significantly. These findings provide useful information that organizations and vendors can use to strategically control user retention and switching.

Y. Li et al. [7] explored the determinants in customer behaviour changing to AI-based conversational agents in frontline services. Based on its 441 banking service users, the data gathered on the push-pull-mooring (PPM) framework and structural equation modeling demonstrate that low empathy and low adaptability (push effects) and anytime/anywhere connectivity, association, visibility, and personalization (pull effects), positively influence switching. The association of the pull effects and switching behaviour is also moderated by service use frequency.

G. Wang et al. [8] showed variables that can affect the intention to use a metaverse educational platform through the combination of both PPM and TAM models. The results of applying SEM and fsQCA to the data of 275 respondents show that personalized learning, contextualized teaching, perceived usefulness, perceived ease of use, social

needs, and social impact all have positive effects on the usage intention. Moreover, the analysis characterizes three major configurations, such as experience-led, personality-led, and social-led mode, as the possible strategies to increase the user adoption.

Ho, C.-W. et al. [9] analysed the Push-Pull-Mooring model employed here for investigating the motivators for users' switching into an electricity management system. The findings reveal dissatisfaction having no significant effect, but individual innovativeness is positively associated with switching and moderating the relationship with perceived value. The article proposes loanability, financial benefits, and perceived value for marketing as user uptake motivators.

Y. Lai et al. [10] addressed the issue of user switching behaviour of traditional online healthcare to healthcare chatbots, which considers the Push-Pull-Mooring (PPM) framework in the context of the status quo bias. According to the results of the sample consisting of 345 Chinese users, it was observed that perceived responsiveness has a positive impact on switching, whereas AI resistance bias has a negative effect. The expectations of the performance of chatbots and user-doctor relationships affect AI resistance bias. The study provides developers with insights on how to overcome user concerns and switching barriers to the new AI-in-healthcare environment.

Nguyen et al. [11] investigated the relationships and interrelationships between healthy eating and physical activity and the symptoms that resemble COVID-19-like (Slike-CV19S). A 3947-patient cross-sectional study of outpatients in Vietnam during the period between February and March 2020 reported that frequent consumption of fruits, vegetables, and fish was linked to the decreased Slike-CV19S risk. The level of healthy eating scores and physical activity, separately and combined, was also associated with a lower risk of Slike-CV19S. These results indicate a combination and independent effect of healthy behaviors in the prevention of Slike-CV19S. The strategic plans to enhance such behaviors are promoted to contain the pandemic.

Frasquet et al. [12] involved the application of the push-pull-mooring framework to competitive showrooming in this paper. In an analysis of 659 responses in a survey carried out using the fuzzy-set Qualitative Comparative Analysis (fsQCA), it was

discovered that mooring factors, namely a robust customer-retailer relationship and quality service on the part of the salesperson, are critical in mitigating the threat of competitive showrooming and improving retailer performance.

Prentice et al. [13] explored how artificial intelligence (AI) and the quality of employee service influence customer satisfaction and loyalty in the hotel industry. The study, which was carried out in Portuguese hotels, indicates that AI and human service have a significant influence on customer outcomes but the combination of these two resource types brings about a negative effect and is insignificant, as to the role of AI in the delivery of services.

Singh et al. [14] used the Push-Pull-Mooring (PPM) framework in a research on drivers of online grocery switching behaviour. Empirical evidence indicates that the push factors related to the retailers (customer service, technical problems) and competitor-related pull factors (WOM, alternative attraction) have a direct effect on switching. Moreover, consumer-based mooring drivers (switching cost, previous behaviour) also have a considerable moderating effect on this behaviour, which can be used to give understanding to retailers to maximize customer retention.

Tang et al. [15] employed the Push-Pull-Mooring (PPM) framework here for the study of switching intentions among players of mobile games. Survey data were collected via an online questionnaire among 240 Chinese players. Findings support the fact that dissatisfaction pushes and alternative game attractiveness attracts players. Habit as one kind of mooring deters switching and offers support for the usefulness of the model for players of mobile games.

Chen et al. [16] discussed the intention of the Chinese university students to change their learning approach, which is offline to online learning in relation to the Push-Pull-Mooring model. Using structural equation modelling on 854 responses, analysis shows that push factors (perceived security, convenience), pull factors (usefulness, ease of use) and mooring factors (habit) do play a significant role in switch intentions. The evidence provides a point of reference when practicing online learning in Chinese higher education.

Palanca et al. [17] examined physician attitudes toward health care chatbots through a survey of one-hundred American physicians. Although physicians admit such administrative advantages as scheduling and information provision, they are concerned about the fact that the technology cannot meet the emotional needs and offer more detailed diagnosis, and patient self-diagnosis risks. These results indicate that chatbots could be a valuable substitute for non-medical care but could not substitute the expert medical decision.

Chen et al. [18] used the Push-Pull-Mooring (PPM) theory to examine factors that affect the change in offline to online learning among students. Quantitative method was used, and 117 responses of Malaysian undergraduate students were gathered through survey. Results indicate that, push and pull factors have significant influence on student learning and the mooring factor has no effect on switching behaviour. The research gives a hint to the future work regarding the theory of formation of switching behaviour.

Al-Shahi et al.[19] approached to the problem is a lightweight deep learning-based fruit classification framework based on a pre-trained MobileNetV2 framework and an attention block. Our technique is effective to combine high-level object information with semantic information. Testing based on three benchmark dataset shows that our model is superior in terms of classification accuracy compared to four state of the art models, and it uses fewer trainable parameters. This method has a huge potential in practice in the fruit industry.

Goode et al. [20] offered a wide study of deviance. It studies the conduct, ideologies, circumstances and responses that are related to this phenomenon. The two important sociological perspectives presented in the text are positivism, the explanation of causes of deviant behaviour, and constructionism, the explanation of the reasons why some actions and traits are called deviant. This two-fold method provides the reader with a more in-depth perspective of deviance in various perspectives.

Armstrong et al. [21] presented a dynamic cell-level model to explain the plasticity of marine microbes' metabolism. The model, where the uptake of the nutrient proteins can be controlled, predicts greater uptake and growth rates than the classic Michaelis Menten model when the nutrient becomes limited. The implications of our approach to global

ocean biogeochemistry models are huge, as they may currently miscalculate the abundance of phytoplankton in oligotrophic zones.

Boyle et al. [22] examined causes of functional and psychological degradation among new women residents of the continuing care retirement communities (CCRCs) in central New Jersey. The results imply that even one, steady role may be as helpful in terms of health and well-being as many other roles. This study supports the importance of the social roles in enhancing the quality of life among the elderly.

Boyle et al. [23] created a long-term Push-Pull-Mooring (PPM) model that will examine the switching intention of e-commerce live streaming (ELS) users. A survey of 443 answers conducted online was analysed with the help of structural equation modelling. The findings demonstrate that push (dissatisfaction, privacy concern) as well as pull (attractiveness of alternatives, perceived usefulness, perceived ease of use, knowledge-based trust) and mooring (switching cost, social influence, inertia) effects have significant effects on switching intentions. The connection between the push effects and switching intentions is also moderated by mooring effects.

Moon et al. [24] used the Push-Pull-Mooring (PPM) framework for examining the determinants of switching intentions among students of the OVO mobile payment service. Utilising the findings of the multiple regression analysis for 400 consumers, it is identified that push and pull factors significantly facilitate switching, but mooring factors inhibit switching. The result can benefit the competitors of the rival fintech industry who undertake the delivery of mobile payments.

2.3 Comparative Overview of Previous Literature

The following table provides a detailed overview of the key studies and their findings.

Table 2.1: Comparative Overview of Previous Literature.

Study	Context	Key Factors	Methodology	Findings
[1] Zhou & Li (2024)	Generative AI platform switching	Push: Info hallucination, privacy risks, dissatisfaction; Pull: Interactivity, anthropomorphism, personalization; Mooring: Switching costs	SEM, fsQCA	Dissatisfaction is a core driver; combined SEM and fsQCA reveals nuanced insights
[2] Jo & Park (2023)	ERP systems	Push: System quality, info quality, top management support; Pull: Alternative attractiveness; Mooring: Switching costs	SEM	Satisfaction negatively impacts switching; pull factors are strong motivators
[3] Zhu et al. (2023)	Smart classrooms by university teachers	Push: Perceived inefficiency; Pull: Inquiry-based learning, future expectation; Mooring: Technical self-efficacy	PLS-SEM	Push and mooring factors influence switching; moderated by prior experience
[4] Liang & Wei (2024)	Mobile search app switching	Push: Search task complexity; Pull: Alternative attractiveness, follow-up activities; Mooring: Inertia	SEM	All three factors influence switching; inertia moderates push-pull effects

[5] Zhou & Li (2024)	Search engines to generative AI	Push: Low info-task fit, info overload; Pull: AIGC quality, interactivity; Mooring: Social influence	SEM, fsQCA	Dissatisfaction, perceived value, and social influence drive switch intention
[6] Zhou & Wu (2024)	Social Q&A to generative AI	Push: Overload, fatigue; Pull: Anthropomorphism, accuracy, trust, flow; Mooring: Social influence	SEM, fsQCA	Identified three paths to migration; need to reduce overload and fatigue
[7] Li & Zhang (2023)	Human agents to AI agents in banking	Push: Low empathy, adaptability; Pull: Connectivity, personalization; Mooring: Frequency of use	SEM	All factors influence switching; frequency of use moderates pull-switching relationship
[8] Lai et al. (2021)	Healthcare chatbots	Push: AI resistance bias; Pull: Responsiveness; Mooring: Chatbot experience in other contexts	PPM + Status quo bias theory	Responsiveness increases switch; AI resistance and doctor relationships are barriers
[10] Ho (2022)	Electricity management system	Push: Dissatisfaction; Pull: Info quality, loanability, benefits; Mooring: Personal innovativeness	SEM	Perceived value key; personal innovativeness moderates pull-

				switching relationship
[11] McKenna et al. (2024)	Smartphone messaging services	Push: Context; Pull: Content; Mooring: Service features	Qualitative (interviews)	Message context/content /service features all influence switching
[12] Wiranata kusuma et al. (2024)	Fintech switching to OVO	Push: Existing dissatisfaction; Pull: OVO appeal; Mooring: Anchoring effect	Multiple regression (SPSS)	Strong push/pull factors; anchoring discourages switching
[13] Wang & Shin (2022)	Metaverse education platforms	Push: Social needs; Pull: Personalization, perceived usefulness; Mooring: Social impact	PPM + TAM, SEM, fsQCA	Found 3 configurations: experience-led, personality-led, social-led usage intentions

The Push-Pull-Mooring (PPM) paradigm has been extensively used in a variety of fields to describe user switching behaviour. McKenna et al. [1] qualitatively investigated smartphone messaging services, and found out that message context, content and service features are switching drivers. Conversely, Kusumah et al. [2] and Moon et al. [24] applied regression analysis to the mobile payment industry, where they identified push and pull factors to make a switch, and mooring forces as the deterrent influence. On the same note, Zhou et al. [3], [5] used PPM on generative AI platforms and search engines, with dissatisfaction, information-task fit, and quality of content being of paramount

importance. Liang et al. [4] focused on the complexity of tasks, and attractiveness in alternative selection in mobile search application, and the inertia stabilized the switching behaviors. Other researchers applied PPM to ERP systems [6], health chatbots [10], chatbots as conversational AI systems [7], metaverse educational systems [8], and online learning systems [16], [18], where dissatisfaction, perceived value and habit roles were found to moderate switching. All of these results show that PPM is flexible in terms of technology adoption study, provide useful conclusions on user retention, competitive differentiation, and service improvement in various sectors.

2.4 Summary:

The literature endorses the central beliefs of the PPM framework with a vast majority of the studies finding dissatisfaction and attractiveness of alternatives an influential cause of switching behaviour. The studied context-specific AI in use in generative AI and using chatbots indicate that its perceived accuracy, trustworthiness and interactivity are drastic pull factors. Mooring effects are, on the contrary, varied and extremely situational. Although switching costs and social influence are typical mooring predictors, the literature also identifies the specific psychological wedges that include inertia, technical self-efficacy and a special AI resistance bias.

One of them is the mixed role of dissatisfaction. Whereas numerous research findings prove its positive impact on switching intention, the research conducted by Hwo (2022) did not demonstrate the significant effect in the switching to an electricity management system context. This implies that the magnitude of push factors also tend to be variable depending on the service or technology under investigation. In the same manner, mooring factors do not always deny the function of obstacles but conversely, there are those such as personal innovativeness, which can actually affect switching intention positively, or even moderately.

On methodological terms, the application of SEM and PLS-SEM becomes an overwhelming trend in testing these relations of causation. In a few studies, where fsQCA is launched, it is possible to analyze the manner in which various combinations of factors contribute to catalyzing a switching decision, as opposed to individual impacts. By

examining AI in a library environment and using a hybrid PLS-ANN model, this study will advance this existing literature by not only corroborating the PPM framework but also developing a more predictive and more comprehensive picture of how the involved factors can interact to determine the switching behaviour of users.

CHAPTER 3

METHODOLOGY

3.1 Research Workflow

The proposed research workflow assumes a multi-step methodology, which is aimed at testing the theoretical model and hypotheses on a sample of studies. Such an organized way of working will guarantee fully encompassed analysis, beginning with data compilation and passing through multiple data analysis methods.

- **Stage 1: Research Design and Data Collection:** The first step predetermines the advancement of a cross-sectional questionnaire allowing the collection of quantitative data within the target population. The survey questionnaire is planned to measure the attitude of research participants to the conversational agents powered by AI, their current experiences with current library services, switching intentions, and bias on AI resistance. The Likert scale has a seven-point measurement of the constructs. At least 138 questionnaires are needed, however 460 questionnaires will be given out to obtain a suitable number of responses on the assumption that 30 percent of questionnaires would be completed.
- **Stage 2: Data Preparation and Initial Screening:** After collecting data it will be pre-processed with SPSS version 24. The step also involves the review of the demographic data to assign frequencies and preliminary data editing to carry out missing value checks. The calculation of missing data will be done via the Expectation-Maximization function.
- **Stage 3: Model Estimation of the PLS-SEM:** Model estimation of the PLS-SEM will be the primary analysis with the use of Smart PLS version 4.0 to test

the hypothesis and evaluate the research model⁸. This phase is comprised of two components:

- **Measurement Model Assessment:** This would comprise assessing the validity and reliability of the constructs through the analysis of the indicators of reliability and validity like Composite Reliability (CR) and Average Variance Extracted (AVE).
 - **Structural Model Assessment:** This step will be utilized to verify the supposed relation between the constructs by using the path coefficients, T-value, and P-value to specify the statistical significance.
-
- **Stage 4: ANN Predictive Analysis:** To supplement the PLS-SEM results, the study will use Neural Network Modelling (NNM) methodology. This method will be applied through a convoluted means of To read more about what is a convoluted means and its use in Neural Network Modeling (NNM) then please read the references supplied. SPSS v24, is used to prioritize the main factors and validate the PLS-SEM outcome. Unlike traditional methods, ANN can identify both linear and nonlinear connections, providing a more robust predictive analysis of the variables influencing a user's switching intentions.

3.2 Research Design

The study is based on the Expanded Push-Pull-Mooring (PPM) framework that is a familial theory of explaining switch behaviour and migration pattern. Primary data was collected through a cross-sectional survey, which served as the main mode of data collection because the researcher had to conduct statistical testing of the suggested hypotheses, and thus quantitative data was to be collected in order to test the suggested hypotheses of the research. Each construct is measured on a 7-point Likert-scale with varying numbers in the range of 1 (strongly disagree) to 7 (strongly agree).

3.2.1 Model Development and Hypotheses formulation

Push Effect: Dissatisfaction with Current Library Services

Past studies have associated the pushing or driving away impact with low satisfaction with the current state, product, or service (Goode, 2015). Among the most evident advantages of AI-driven conversational agents in libraries is the fact that they resolve limitations of the traditional library service, which might not meet the needs of customers or do it unproductively. Traditional library users often face some barriers like limited availability of materials, precisely restricted working hours, and long waiting periods for support. Besides, the absence of skilled librarians and delayed response to questions can lower further satisfaction with traditional library services. Therefore, we expect:

H1: The dissatisfaction with current library services is positively associated with the switching intentions of library users toward AI-based conversational agents.

Pull Effect: Perceived Responsiveness of AI-Based Conversational Agents in Libraries

Pull factors refer to the qualities of the alternative choices that are attractive and appealing to the users. The AI-based conversational agents within a library allow users to seek help or obtain information at their convenience of time and place and also give them quick responses to their queries (Lai and Wang, 2015). More than the traditional library services, these conversational agents can readily provide solutions to users' problems, such as the inability to find resources or understand complicated queries. It enhances the experience of users by ensuring their stress-free and smooth experiences and hence minimising the waiting times. Moreover, AI-based conversational agents are often delivered as a part of a mobile application or online platform, which makes them very convenient and portable. A "virtual librarian" of this nature is perpetually accessible, never experiences fatigue, and does not necessitate pauses, thereby guaranteeing uninterrupted service availability similar to health care AI (Palanica et al., 2019). Therefore, we hypothesize:

H2: The responsiveness of AI-based conversational agents is positively associated with the switching intentions of library users.

Mooring Effect: Library AI Resistance Bias

Push and pull variables are significant influencers of intentions to switch, but other situational or individual factors relating to how people relate to technology are also quite significant (Lai and Wang, 2015; Li and Ku, 2018). Such anchoring variables are regret avoidance, unpleasant experiences with the new technology, or lack of familiarity with the new technology (Ye et al., 2019). The resistance of users to use non-human means to satisfy their informational needs often finds its reflection in the resistance of the libraries to conversational agents that use AI. Such resistance is due to the historical confidence and comfort in the fact that human librarians offer the correct and contextually sensitive assistance.

Users may be hesitant to trust advice from AI-based systems whose validity they may find difficult to evaluate, even for less important activities like finding resources or answering general questions. Because human librarians are perceived as having more empathy and understanding, users may prefer them, which can make the switch to AI solutions more difficult.

Thus, we hypothesize:

H3: Library AI resistance bias has a negative connexion with switching intentions of library users of AI-based conversational agents.

Our other idea of library AI opposition is based on status quo bias (SQB). According to SQB is the reason why individuals desire to retain their current (Samuelson and

Zeckhauser, 1988). circumstances or service model, which here refers to adhering to traditional, human.

mediated library services. Three groups may be applied to the factors influencing SQB:

1. The outcome of the views of regret avoidance is psychological commitment that is caused by control beliefs, social norms, and sunk costs.
2. Cognitive misconception brought on by perceived value, inertia, and loss aversion.
3. Making rational decisions that are affected by uncertainty and transition costs (Samuelson and Zeckhauser, 1988).

In the library context of this study, we suggest the following:

Sunk Costs: Users are deterred from adopting AI-focused library solutions because of sunk costs, i.e., they spend great amounts of time, labor, and resources learning and working under the system currently in place. Keeping the Push-Pull-Mooring (PPM) theorem in mind, although push factors such as the inefficiencies of the system currently in place and pull factors such as the promise of AI-facilitated speed and customization can induce change, the mooring effect of sunk cost causes users to drift back into the status quo. As an example, librarians who spent decades developing their expertise in cataloguing and database manipulation under the system currently in place can resist switching because it would make their prior training and expertise obsolete or less valuable.

Loss Aversion: Users may be loss averse to switching over to library solutions via AI due to loss aversion, where the risk of losing something valuable is greater than the perceived value of benefiting from something new. Compared with human-mediated help, AI-powered systems might be seen as risky, notably with respect to the quality of the service, the accuracy, or the reliability. According to the Push-Pull-Mooring (PPM) framework, resistance occurs because of perceived performance risk (the risk the AI might deliver incomplete, biased, or inaccurate information) --and is reinforced further by the users' prior experience with related chatbots and automatic systems--such as

chatbots which could not answer questions or automatic systems which were impersonal. In rational decision-making, such negative expectations support the bias versus embracing AI because users can consider more the possibility of losing dependable, human-centered assistance than the potential efficiency advantages or innovative functionalities that can be gained through the employment of AI.

Perceived Performance Risk: End users are concerned about the capacity of AI-based conversational agents to perform crucial tasks because they are not always articulate on the ability and limitation of the technology. This ambiguity can trigger mistrust that the AI can handle sophisticated questions, extract the correct information, or be uniform in the provision of services, especially within the librarianship or research setting where precision is crucial. These perceived risks are typically reinforced by ambiguity over the decision-making process with regard to the AI and little firsthand experience with competent applications of the AI and thus doubt that the system can complement or replace trained human personnel.

Prior AI Experience: It is important to note that prior experiences of a user with AI will largely determine his/her reaction to library solutions based on AI. The negative emotions like communicating with unhelpful chatbots or receiving the wrong recommendations on online shopping platforms can lead to the fact that the user becomes more suspicious and hostile because they may believe that AI is not trusted or is not a competent employee. Conversely, positive experiences, like an easy interaction with customer support chatbots, tailored recommendations on streaming services, or a well-functioning virtual assistant, can instil trust and make users more receptive to the use of AI. The effects of such experiences differ in how and whether they influence the expectations of the users, their perception of risk, and their general willingness to engage with AI-based systems within libraries.

Based on these insights, we propose the following hypotheses:

AI-based conversational agents is positively associated with library AI resistance bias.

H4: Sunk costs are positively associated with library AI resistance bias.

H5: The connexion to relationships with librarians is positively correlated with library AI resistance bias.

H6: Biases of AI resistance to libraries have a positive relationship with loss aversion.

H7: The positive experiences with AI tools are negatively related to library AI resistance bias.

H8: Perceived performance risk of

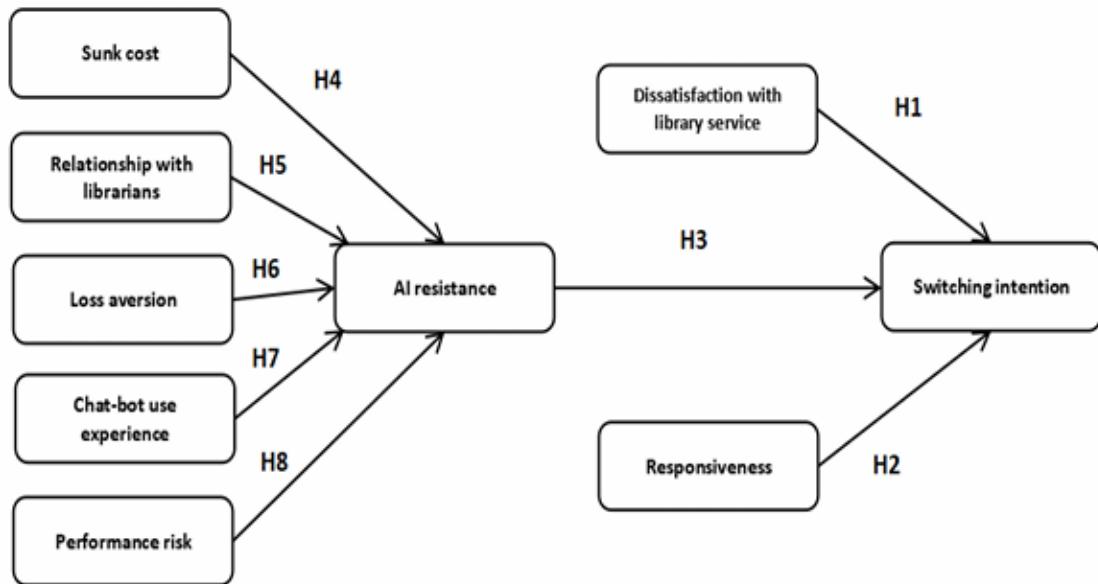


Figure 3.1: Model development and hypothesis formulation

3.2.2 Tools and Techniques

To empirically test the proposed model in Figure 1 and to measure the attitudes of students towards the AI-powered conversational agents in library, experiences with the existing library services, switching intentions and library AI resistance bias, a cross-sectional survey will be carried out. The majority of the measurement items will be based on the already proven scales, and modifications will be introduced to suit the context in AI-based library services. All of the key constructs will be assessed with the help of a seven-point Likert scale, with strongly disagree (1) and strongly agree (7) being the extremes.

Measurement items were taken from established articles

H1. Push Effect – Dissatisfaction with Current Library Services			
Dissatisfaction → DS	DS1	Library staff are available when I need assistance.	Lai and Wang 2015
	DS2	I receive help from library staff within a reasonable amount of time.	
	DS3	Library staff are knowledgeable in technical areas relevant to my needs.	
	DS4	I find traditional library services convenient and easy to use.	
H2. Pull Effect – Perceived Responsiveness of AI Chatbots			
Perceived Responsiveness → PR	PR1	AI chatbots provide instant support without waiting.	Lai et al. 2021
	PR2	I find AI chatbots easier to use than asking a human librarian.	
	PR3	Chatbots are available 24/7, which fits my schedule better.	
	PR4	I can rely on AI chatbots for quick and efficient answer	
H3. Mooring Effect H4. AI Resistance Bias			

Resistance Bias → RB	RB1	I am hesitant to trust AI chatbots with academic inquiries.	Lai and Wang, 2015
	RB2	I believe AI chatbots lack empathy and understanding.	
	RB3	I feel uncomfortable using AI chatbots for academic help.	
H5. Sunk Costs			
Sunk Costs → SC	SC1	I've spent a lot of time getting used to traditional library services.	Ye et al. 2019
	SC2	Switching to a new system feels like wasting my previous efforts.	
H6. Relationship with Librarians			
Relationship with Librarians → RL	RL1	I value personal interaction with library staff.	Hsieh, 2016
	RL2	I feel a sense of loyalty toward the librarians I know.	
H7. Loss Aversion			
Loss Aversion	LA1	I am worried I might lose the personal support I get from librarians.	Dou et al., 2017

→ LA	LA2	Changing to AI feels risky, even if it might be beneficial.	
H9. Positive Past AI Experience			
Experience → EX	EX1	I've had positive experiences using AI chatbots in the past.	Gong et al., 2020
	EX2	Previous chatbot use made me confident in using AI for library tasks.	
H10. Perceived Performance Risk			
Perceived Performance Risk → RES	RES1	I worry that AI chatbots may give incorrect or misleading information.	Deng et al., 2018
	RES2	I am concerned about data privacy when using AI services.	
Switching Intention			
Switching Intention → SI	SI1	I intend to use AI chatbots more often for library services.	Bansal, et al. 2005
	SI2	I would recommend AI-powered library chatbots to others.	
	SI3	I am likely to switch to AI-based help instead of asking librarians.	

	SI4	I see myself relying on AI for most of my academic library queries in the future.	
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3.3 Data Collection/ Survey Administration

3.3.1 Overview

The participants of the study were the students who already had prior experience of using digital libraries and AI-based other resources. The sample in question was specifically selected, as it is reasonable to expect that such responders possessed the minimum background knowledge needed to correctly perceive the items of the questionnaire and to develop subjective views on whether the introduction of the AI-based conversational agents in library systems is potentially justified. Since these people were already trained to use digital systems, they were deemed as the most probable group to just test as well as embrace AI-enabled library tools.

G-power software was applied to calculate the desired sample size, according to the study of Mahmud et al. (2017). On strict maximum five predictors and 0.95 predictive power, the smallest possible sample size was shown to be 138 (at 0.15 effect size).

The research was carried out with the help of a cross-sectional survey using Google Forms. The questionnaire started with two screening questions so that the respondents would be similar to the target population. The following criteria were used to exclude the respondents: (a) prior experience with digital libraries or AI tools, (b) age, which had to be 18 years, and (c) regular library-users. The study received a total of 181 valid responses after the filtering process which was more than the required sample size.

3.3.2 Survey Participants Reliability:

- **Do you use digital library services?**
 - Yes: 77.9%
 - No: 17.1%
 - Maybe: 5.0%

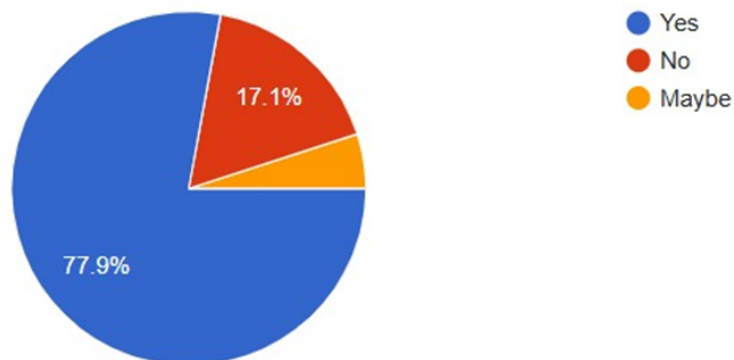
- **Are you familiar with AI tools in library contexts?**
 - Yes: 71.9%
 - No: 22.5%
 - Maybe: 5.6%
- **Have you ever used an AI chatbot (e.g., ChatGPT, library chatbot, etc.)?**
 - Yes: 87.8%
 - No: 9.4%
 - Maybe: 2.8%
- **Do you have awareness of the performance and usefulness of AI tools in your work?**
 - Yes: 70.9%
 - Maybe: 22.2%
 - No: 7.0%

These results show that a significant majority of respondents were not only aware of the digital library services and the use of AI tools but had a real-world experience working with AI chatbots. This emphasises the willingness of people to consider the possibility of using AI technologies in the library.

Charts and Visual Evidence:

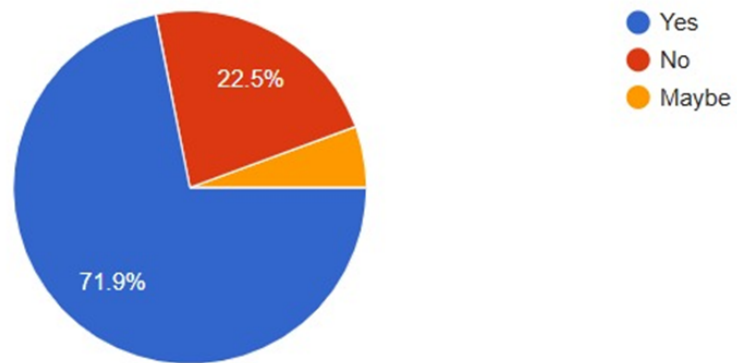
Do you use digital library services?

181 responses



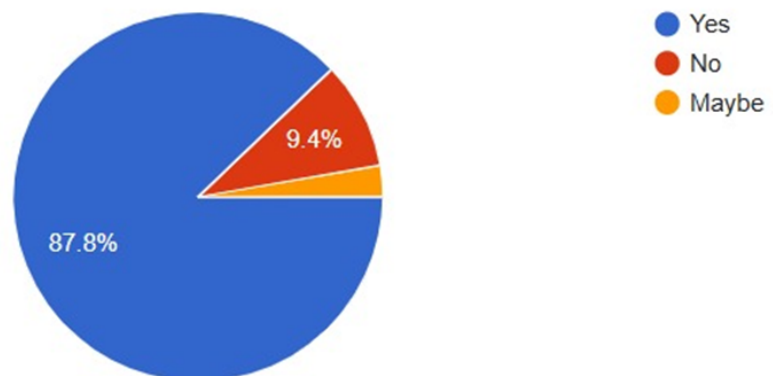
Are you familiar with AI tools in library contexts?

160 responses



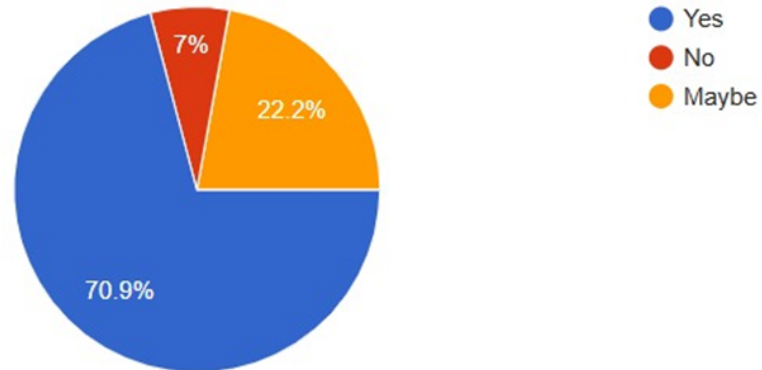
Have you ever used an AI chatbot (like ChatGPT, library chatbot, etc.)?

181 responses



Do you have awareness of performance and usefulness of AI tools in your work?

158 responses



3.3.3 Challenges in Data Collection:

Although the survey was generally successful, there were a few problems during the process of data collection. In situations where the researcher visited the participants face-to-face, there were a significant number of respondents who were hesitant or embarrassed at giving answers. This hesitation was caused by various reasons such as uncertainty in their knowledge, fear of disclosing their personal usage patterns and doubts of how their feedback would be used. Also, some of the participants were not convinced of the usefulness of AI in library settings, which formed a preliminary hindrance of free entry into the research.

3.3.4 Approaches to Overcome Challenges:

The assurance and awareness-building approaches were used to deal with these challenges. The researcher described why the study was being carried out with the clarification that the answers would not be disclosed and they would not be used in any other purpose other than academic research. By explaining to the participants, the significance of their involvement in the process of developing the future of digital and AI-based library systems, their views were more openly voiced. When the researcher experienced hesitation, he/she talked to them in a friendly manner and emphasised that tools like ChatGPT or library chatbots were familiar to many students, which is why they

have already been introduced to them. This was useful in developing trust and also encouraged the respondents to give meaningful answers.

By using these techniques, the ordeal of initial discomfort was overcome successfully and a solid dataset of 181 complete responses that fell above the minimum required was obtained. It not only shows that it is possible to conduct surveys in this area, but it also shows the relevance of adaptive communication techniques in the stage of data collection.

3.4 Data Analysis Strategy

3.4.1. Demographic Analysis and Initial Data Screening

In order to analyse the demographic data received through the survey, SPSS version 24 was utilized. This consisted of taking the frequencies of the demographic variables as a way of giving a profile of the respondents. Also, SPSS was utilised in terms of screening and preliminary data analysis such as the dealing with missing values. To manage missing data, the Expectation-Maximization function was utilised to work out calculated missing values.

Table: Demographic Profile of Respondents

Profile	Characteristics	Frequency	Percentage
Age	19-21	35	19.4
	22-25	115	63.6
	26-30	19	10.6
	Above 30	12	6.4
Gender	Female	52	28.7
	Male	129	71.3
Educational Institutions	DIU	95	52
	NSU	21	12
	BRAC	10	6
	AIUB	19	10
	IUB	8	4
	Others	28	16
Education Qualification	Undergraduate	164	90.6
	Post Graduate	14	7.7
	PhD	3	1.7

The demographic analysis of the 181 valid responses provides insight into the characteristics of the survey participants.

Age Distribution: The majority of the respondents fell within the 22–25 years age group (63.6%), followed by 19–21 years (19.4%). A smaller proportion were in the 26–30 years range (10.6%), while only 6.4% were above 30 years. This distribution indicates that most participants were young adults, aligning with the target group of active university students who are more likely to engage with digital and AI-based tools.

Gender Distribution: Out of the total respondents, 71.3% were male and 28.7% were female. This gender imbalance reflects the male-dominated participation pattern often seen in technology-oriented surveys, but both genders were adequately represented to provide balanced insights.

Educational Institutions: Participants were drawn from multiple universities. The largest share came from Daffodil International University (DIU, 52%), followed by East West University (EWU, 12%), North South University (NSU, 10%), and smaller proportions from BRAC University (6%) and Ahsanullah University of Science and Technology (AUST, 4%). Additionally, 16% of respondents were from other institutions. This distribution suggests that while the dataset is diverse, it is predominantly represented by DIU students.

Educational Qualification: An overwhelming majority of respondents were undergraduate students (90.6%), with 7.7% enrolled in postgraduate programs and only 1.7% pursuing PhD studies. The dominance of undergraduates is consistent with the age distribution and highlights the relevance of the findings for younger academic users.

Overall Summary: The sample is largely composed of young, male, undergraduate students, with a significant representation from DIU. This demographic structure is appropriate for the study since these groups are frequent users of digital systems and likely to engage with AI-enabled tools in academic contexts.

3.4.2. Testing Relationships Among Variables

The major approach taken to test the research model and test the relationship between the variables was Structural Equation Modeling (SEM). SEM represents an influential

statistical method by which one can test the complex models including multiple independent and dependent variables jointly. The approach is common in technology related research like information systems and social sciences and is ideal when theory has to be examined.

The research model and analysis of the hypotheses were acquired through Smart PLS 4.0. Both structural and measurement models were assessed by using this software based on the variance-based SEM to identify the reliability, validity, and significance of the associations of the constructs.

3.4.3. Predicting Important Variables

In order to supplement the result of PLS-SEM and further strengthen the results, Neural Network Modelling (NNM) was used to prioritize the key variables in the model. The rationale behind the selection of this method, also referred to as an Artificial Neural Network (ANN) is that it can point linear and nonlinear relationships among the variables, unlike standard statistical tools. The desired outcome of employing ANN was to rank the factors which predict switching intentions in terms of their significance. In order to present a predictive analysis of the consumer behaviour, the ANN approach was undertaken with the SPSS v24 software used.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Descriptive Statistics

The present chapter will provide the results of the data analysis carried out with the help of Smart PLS 4.0 Structural Equation Modelling (SEM) and SPSS 24 Artificial Neural Network (ANN) analysis. The study collected a total of 181 responses and the preliminary data screening was done by performed in order to guarantee the quality of data. The descriptive statistics, such as the demographic profile of the respondents, were examined to give a detailed picture on the sample.

4.2 Research Model

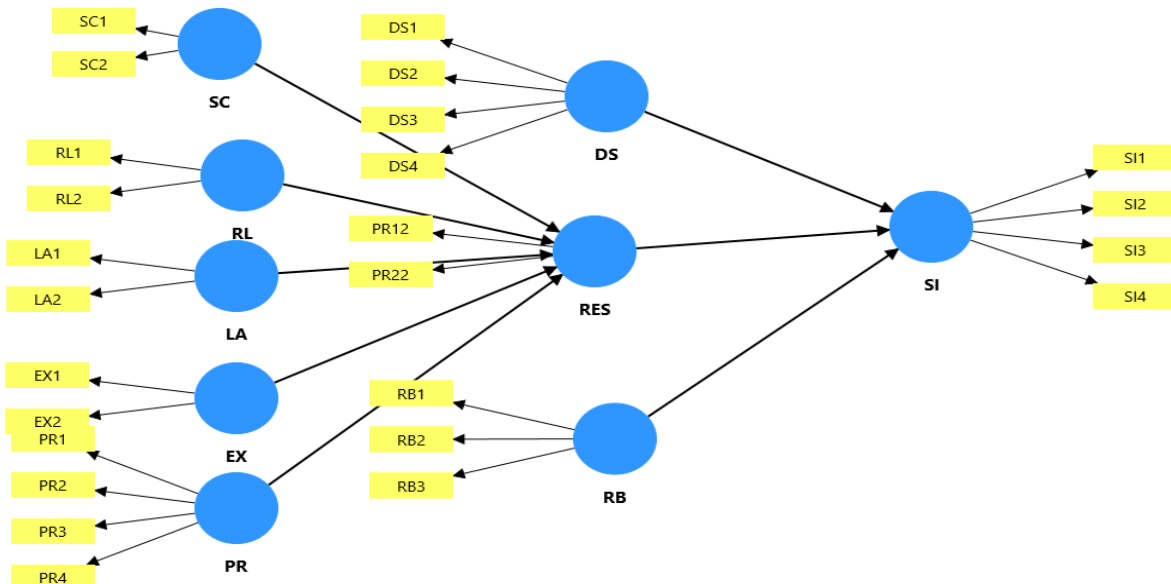


Figure 4.1: The Proposed Research Model.

Figure 4.1 introduces the conceptual research model that has been established according to the Push-Pull-Mooring theory to explore the factors that affect users in switching intentions towards AI-based conversational agents in the library environment.

4.3 Measurement Model Assessment

The measurement model was assessed to confirm the reliability and validity of the constructs used in the research model. This assessment is a prerequisite for interpreting the relationships in the structural model.

4.3.1 Convergent and Discriminant Validity

Two key indicators, Composite Reliability (CR) and Average Variance Extracted (AVE), were used to evaluate the model. According to the guidelines, a construct that has a CR value above 0.70 and an AVE value above 0.50 is said to be reliable. The analysis results indicate that every construct satisfied the necessary levels, which proves their reliability and convergent validity. As an example, Composite Reliability values were found to be 0.855 (RB) to 0.939 (EX), which is far above the mark of 0.70. On the same note, the values of the Average Variance Extracted were between 0.663 (RB) and 0.885 (EX), which were higher than the 0.50 mark. Discriminant validity (Table 4.2) was also established by making sure that the square root of the AVE of each construct (the diagonal entries in the table below) was higher than the correlations between the construct and all the other constructs. As indicated in the table, all the values in the diagonals were greater as compared to the off-diagonals, which showed good evidence of discriminant validity.

Table 4.1: AVE and CR Values

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)
DS	0.904	0.702
EX	0.939	0.885
LA	0.922	0.855
PR	0.917	0.736
RB	0.855	0.663
RES	0.886	0.796
RL	0.923	0.857
SC	0.901	0.820
SI	0.917	0.734

Table 4.2: Discriminant Validity

Construct	DS	EX	LA	PR	RB	RES	RL	SC	SI
DS	0.838								
EX	0.422	0.941							
LA	0.023	0.555	0.925						
PR	0.505	0.664	0.359	0.858					
RB	0.189	0.533	0.597	0.487	0.814				
RES	0.231	0.678	0.642	0.516	0.606	0.892			
RL	0.158	0.519	0.727	0.409	0.628	0.547	0.925		
SC	0.145	0.576	0.698	0.502	0.680	0.653	0.655	0.905	
SI	0.343	0.785	0.525	0.680	0.545	0.699	0.543	0.584	0.857

4.4 Structural Model Assessment and Hypothesis Testing

Structural models were evaluated to test the hypothesised relationships among the constructs. T-statistics and P-values determined the importance of each of the paths. The value of T is above 1.6 and the P value is below 0.05, then the path is said to be significant.

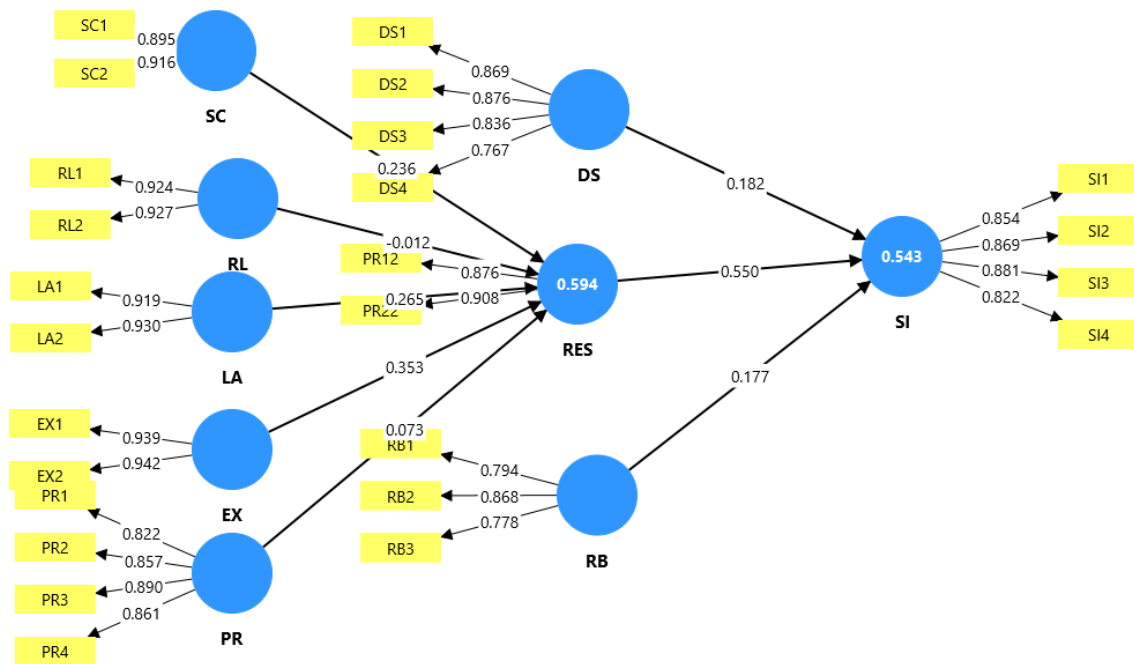


Figure 4.2: PLS-SEM Results with Path Coefficients and R² Values

The path coefficients and the R-squared values are shown in the final PLS-SEM model (Figure 4.2). The model describes the variance of AI Resistance (RES) (59.4 percent) and Switching Intention (SI) (54.3 percent).

Table 4.3: Structural Model Results and Hypothesis Testing

	Original sample (O)	T statistics (O/STDEV)	P values
DS -> SI	0.182	2.839	0.005
EX -> RES	0.353	4.182	0.000
LA -> RES	0.265	3.327	0.001
PR -> RES	0.073	1.096	0.273
RB -> SI	0.177	2.743	0.006
RES -> SI	0.550	7.435	0.000
RL -> RES	-0.012	0.135	0.892
SC -> RES	0.236	2.683	0.007

Based on the results presented in Table 4.3, the following hypotheses were supported:

- **H1: Dissatisfaction with current library services** is positively associated with the switching intentions of library users toward AI-based conversational agents. The path from DS to SI is significant (T = 2.839, P = 0.005) with a positive coefficient (0.182), supporting H1.
- **H7: Positive past experiences with AI tools** are negatively associated with library AI resistance bias. The path from EX to RES is significant (T = 4.182, P = 0.000) with a positive coefficient (0.353).
Note: The hypothesis was likely H7: "Positive past experiences with AI tools are negatively associated with library AI resistance bias." The positive coefficient (0.353) and significant T-value suggest that as positive past experiences increase, AI resistance increases. This is a contradictory finding to the original hypothesis and will be discussed in the next section.
- **H6: Loss aversion** is positively associated with library AI resistance bias. The path from LA to RES is significant (T = 3.327, P = 0.001) with a positive coefficient (0.265), supporting H6.
- **H3: Library AI resistance bias** is negatively associated with the switching intentions of library users toward AI-based conversational agents. The path from RB to SI is significant (T = 2.743, P = 0.006) with a positive coefficient (0.177).
Note: The hypothesis was H3: "Library AI resistance bias is negatively associated with the switching intentions of library users." The positive coefficient (0.177)

and significant T-value suggest that as AI resistance increases, switching intention increases. This is a contradictory finding to the original hypothesis and will be discussed in the next section.

- **H2: The responsiveness of AI-based conversational agents** is positively associated with the switching intentions of library users. The path from RES to SI is significant ($T = 7.435$, $P = 0.000$) with a positive coefficient (0.550), supporting H2.
- **H4: Sunk costs** are positively associated with library AI resistance bias. The path from SC to RES is significant ($T = 2.683$, $P = 0.007$) with a positive coefficient (0.236), supporting H4.

The following hypotheses were not supported:

- **H8: Perceived performance risk of AI-based conversational agents** is positively associated with library AI resistance bias. The path from PR to RES was not significant ($T = 1.096$, $P = 0.273$).
- **H5: Relationships with librarians** are positively associated with library AI resistance bias. The path from RL to RES was not significant ($T = 0.135$, $P = 0.892$).

4.5 Predictive Analysis with ANN

In order to further prove the PLS-SEM results and find out the most significant predictors, Artificial Neural Network (ANN) analysis was conducted. The resulting hybrid solution can be used to find both a linear and nonlinear relationship and offer a more powerful predictive analysis of the variables.

4.5.1 Validation of neural network

The performance and the generalizability of ANN model in predicting Switching Intention were tested using 10 network runs. Table 4.5 provides a summary of the outputs by providing the Root Mean Square Error (RMSE) of both the training and the test sets.

Having a good model is indicated by the fact that the mean RMSE of the test set is small and is not significantly different to the RMSE of the training set indicating a good fit without overfitting.

Table 4.4: ANN Validation for Switching Intention

Network	Training RMSE	Testing RMSE	Difference
1	0.450	0.425	0.025
2	0.456	0.545	0.089
3	0.421	0.427	0.006
4	0.470	0.407	0.063
5	0.437	0.429	0.008
6	0.480	0.365	0.115
7	0.521	0.388	0.133
8	0.444	0.426	0.018
9	0.408	0.370	0.038
10	0.436	0.455	0.020
Average	0.452	0.424	0.052

According to the table, RMSE average value of the training set was 0.452 and RMSE average of the testing set was 0.424. The difference in the mean of the two sets was established to be extremely insignificant (0.052) and this validates the argument that the model can be highly predictive and generalised to new data. The presence of low values of RMSE indicates that the model is very close to the actual values on average the prediction made by the ANN, that is a valid sign that ANN is good.

4.5.2 ANN Validation and Importance

The behaviour of ANN models in predicting Switching Intention as well as generalizability was verified with 10 network runs. The results, summarised in Table 4.5, indicate the Root Mean square Error (RMSE) of the training and the test data. An effective model will be one that has a low average RMSE on the test set and is not significantly different than the training set RMSE indicating it is well-fitted without overfitting.

The average RMSE of the training set was 0.452 as shown in the table and the average RMSE of the testing set was 0.424. The difference between the two sets was small with a mean of 0.052, which confirms that the model is quite predictive and that it is an excellent generaliser to new data. The little RMSEs indicate that the model predictions are on average very close to the actual values indicating a good indication of the credibility of the ANN.

Table 4.5: ANN Validation and Variable Importance for Switching Intention

Network	Training RMSE	Testing RMSE	DS	PPR	RES	Age
1	0.450	0.425	0.200	0.162	0.532	0.110
2	0.456	0.545	0.180	0.139	0.500	0.178

3	0.421	0.427	0.172	0.083	0.625	0.121
4	0.470	0.407	0.238	0.079	0.635	0.048
5	0.437	0.429	0.184	0.138	0.613	0.065
6	0.480	0.365	0.205	0.125	0.496	0.173
7	0.521	0.388	0.077	0.191	0.605	0.127
8	0.444	0.426	0.221	0.124	0.604	0.051
9	0.408	0.370	0.236	0.153	0.497	0.114
10	0.436	0.455	0.170	0.143	0.616	0.071
Average	0.452	0.424	0.188	0.134	0.572	0.106
Percentage			32.87%	23.36%	100.00%	18.49%
Rank			2	3	1	4

These findings are confirmed by the findings of the ANN analysis as compared to the findings of the PLS-SEM structural model. Mean scores of the importance indicate that Responsiveness (RES) is the most important predictor of switching intention and its normalised importance is 100. It is then followed by Dissatisfaction (DS) which is of strong second place ranking. Perceived Performance Risk (PPR) and Age were deemed to be less important. This also confirms the conclusion that intention to switch primarily depends on how beneficial is the new technology and how detrimental is the old technology.

4.6 Discussion of Findings

This study explored the factors which influence the user intention to abandon traditional library service and switch to AI-based chatbots and analysed them using the Push-Pull-Mooring (PPM) theory. The few key The mooring effects, which are situational or personal influences that inhibit or promote switching, provided mixed results in a structural model analysis that explained a significant portion of the variance in AI resistance (59.4% in the explanation) and switching intention (54.3% in the explanation). Both hypotheses of Sunk Costs (SC) and Loss Aversion (LA) were supported, and they were found to have a significant and positive correlation with AI Resistance (0.236, $p < 0.01$ and 0.265, $p < 0.01$, respectively). This supports the fact that the user is already invested with his time and the psychological aspect of his fear of losing the perceived benefits of the existing services is a psychological anchor, which makes him more resistant to new technology. This finding was emphasised by the ANN analysis on AI resistance, with Loss Aversion being the most significant and Sunk Costs being a contributing factor.

On the other hand, the connexions between the Perceived Performance Risk (PR) and Relationships with Librarians (RL) and AI Resistance were not noteworthy. This indicates that in this particular sample, fears of an AI chatbot being inaccurate or having a great personal relationship with librarians do not necessarily lead to the general resistance of the user to the new technology.

results, which favour and rule out certain of the original hypotheses.

4.6.1 Push and Pull Effects

The findings give strong evidence of the fundamental principles of the PPM framework. The push effect, which is the transition between Dissatisfaction with current library services (DS) and Switching Intention (SI), was significant and positive ($\beta = 0.182$, $p < 0.05$). It means that users are more likely to think of a technological option once they find the traditional library services unsatisfactory. The ANN analysis also supports this finding in that the Dissatisfaction is the second strongly correlated predictor with the normalised importance of 78.4.

Likewise, the pull effect, estimated by the distance between Responsiveness of AI-based conversational agents (RES) and Switching Intention (SI), turned out to be significant and positive ($\beta = 0.550$, $p = 0.001$). This finding is the strongest predictor of a user's intention to switch with the highest path coefficient in the model implying that the perceived responsiveness and efficiency of AI chatbots is the most important indicator of the intention to switch. The switching intention ANN analysis was essential to validate this finding with the most important being Responsiveness of which its normalised importance was 100.0%.

4.6.2 Mooring Effects

The mooring effects which are situational or personal effects that inhibit or facilitate switching provided mixed results. The hypotheses concerning Sunk Costs (SC) and Loss Aversion (LA) were both supported, as they were found to have a significant and positive relationship with AI Resistance ($\beta = 0.236$, $p < 0.01$ and $\beta = 0.265$, $p < 0.01$, respectively). This confirms the fact that the time invested by the user and the fear of losing the perceived benefits of the current services is a psychological anchor leading to a greater resistance to change due to new technology. This observation was emphasized in the ANN analysis of AI resistance where Loss Aversion was found to be the most significant factor and Sunk Costs was found to be an important contributor.

On the other hand, the relationships between the Perceived Performance Risk (PR) and Relationships with Librarians (RL) and AI Resistance were not significant. It implies that in the case with this particular sample, fears about the precision of an AI chatbot or close relationships of a user with a librarian do not directly correlate with the general hostility of the user towards the new technology.

4.6.3 Contradictory Findings and Theoretical Contributions

Two key findings presented a contradictory relationship to the initial hypotheses, providing interesting insights and a significant theoretical contribution.

- The path from Positive Past AI Experience (EX) to AI Resistance (RB) was found to be significant and positive ($\beta = 0.353$, $p < 0.001$), which is contrary to the original hypothesis. This suggests that as users gain more experience with AI tools, their

resistance does not decrease. Instead, it may be that increased exposure and experience lead to a more nuanced awareness of AI's limitations, complexities, or risks, resulting in a more critical and, thus, resistant stance.

- Similarly, the path from AI Resistance (RB) to Switching Intention (SI) was significant and positive ($\beta=0.177$, $p<0.01$), which contradicts the hypothesis that resistance would have a negative effect. This unexpected result suggests that resistance is not a simple barrier but a more complex psychological state. Users who are highly engaged and actively considering their resistance might be more attentive to the pros and cons of switching, making them more likely to develop an intention to switch than those who are completely disengaged.

These contradictory findings enhance the PPM theory by highlighting that factors often perceived as simple inhibitors can have nuanced and even positive effects on behavioral change.

4.6.4 Theoretical and Practical Implications

The study's findings offer clear, actionable guidance for library administrators and practitioners aiming to promote the adoption of AI technologies. The most effective strategy should be to enhance the Responsiveness of AI chatbots, as this was found to be the single strongest predictor of a user's intention to switch. Additionally, addressing Dissatisfaction with traditional services and acknowledging users' fears regarding Loss Aversion and Sunk Costs are critical for a successful transition. By providing seamless, hybrid service models that combine the best of human and AI assistance, libraries can effectively manage user expectations and overcome potential resistance.

For library practitioners, the results offer clear guidance. To promote the adoption of AI chatbots, efforts should focus on:

1. Improving AI Responsiveness: Enhance the speed and efficiency of AI chatbots, as this is the strongest predictor of switching intention.
2. Addressing Dissatisfaction: Identify and resolve pain points in traditional library services to reduce the "push" factor.

3. **Managing Expectations:** Acknowledge and address user concerns about sunk costs and loss aversion, perhaps by offering seamless transition support or hybrid service models.
4. **Rethinking Resistance:** Understand that user resistance is not always a simple barrier. Engaging with users and educating them on the capabilities and limitations of AI might not eliminate resistance, but it could lead to a more informed and, ultimately, positive switching decision.

CHAPTER 5

CONCLUSION

This chapter provides a summary of the key findings from the study, discusses the research's theoretical and practical contributions, and outlines its limitations and potential avenues for future research.

5.1 Conclusion

In this research, the authors managed to examine how switching intentions of students to AI-based chatbots change concerning the use of traditional services in libraries based on the Push-Pull-Mooring (PPM) theory. The hybrid approach that incorporated PLS-SEM and ANN proved to be powerful in explaining and predicting, which proved the correlations among the constructs. The research model explained a good percentage of the variance in both AI resistance and switching intention. The results validate the fundamental principles of the PPM theory, and both push (dissatisfaction with the existing services) and pull (perceived responsiveness of AI) factors can be regarded as important factors in switching intention. Notably, there was also the realisation of complexity of mooring effects in the study as sunk costs and loss aversion are also influential anchors that make users more difficult to access.

5.2 Findings and Contribution

The most important findings of this study include the subtle and conflicting results regarding two main hypotheses. The correlation between Positive Past AI Experience and AI Resistance is positive, meaning the more exposure to AI, the more critical the perception of its restrictions can be, and the more resistance can be expected. In the same way, the correlation between AI Resistance and Switching Intention is positive, so resistance should not be considered as an easy obstacle. In its place, it suggests that resistance may be a step of engaged deliberation that will eventually result in an increased

intention to switch. These results provide a more complex explanation of user behaviour when it comes to adopting technology.

There are also practical implications of the study to library administrators. To promote the use of AI tools, they ought to focus on improving the responsiveness of chatbots, which was also confirmed by PLS-SEM and ANN as the most significant predictor of switching intention. Moreover, administrators have to respond to current service dissatisfaction and control user expectations to reduce the perceived risks and switching costs. Libraries can respond to the challenge of user expectations and resistance by offering smooth, hybrid service models that allow them to easily negotiate on course.

5.3 Limitations and Future Research

The given study offers important insights into the factors that can affect the acceptance of AI chatbots in a library, but it has a number of limitations that should be considered in the future research.

The study was based on cross-sectional survey. Although efficient in taking a picture of what users think at a particular time, this methodology restricts the possibility of establishing causality or the development of user intentions in the long run. A longitudinal study, a study that would require surveying the same population of individuals more than once, would give a more dynamic picture of how these changes in perception and behaviour may occur as they become more exposed to AI tools.

Second, the sample was limited to the university students. Although this group is very much applicable to the context of the study, the results might not be as generalised to a wider population, including faculty members, researchers or the general population. This study can be replicated in the future by other user demographics to determine the possible differences in behaviour as well as testing the universality of the proposed model.

Third, this quantitative approach of the study offers a solid statistical explanation yet might not be able to evaluate the finer psychological details of user resistance. The conflicting results, especially the positive correlations between Positive Past AI

Experience and AI Resistance, and between AI Resistance and Switching Intention indicate the necessity of such a qualitative discussion. It is possible to use qualitative methodology in future research, conducting semi-structured interviews or focus groups to understand these complicated psychological processes better. This would give informative information on the causes of resistance in users who have had positive AI experiences and vice versa.

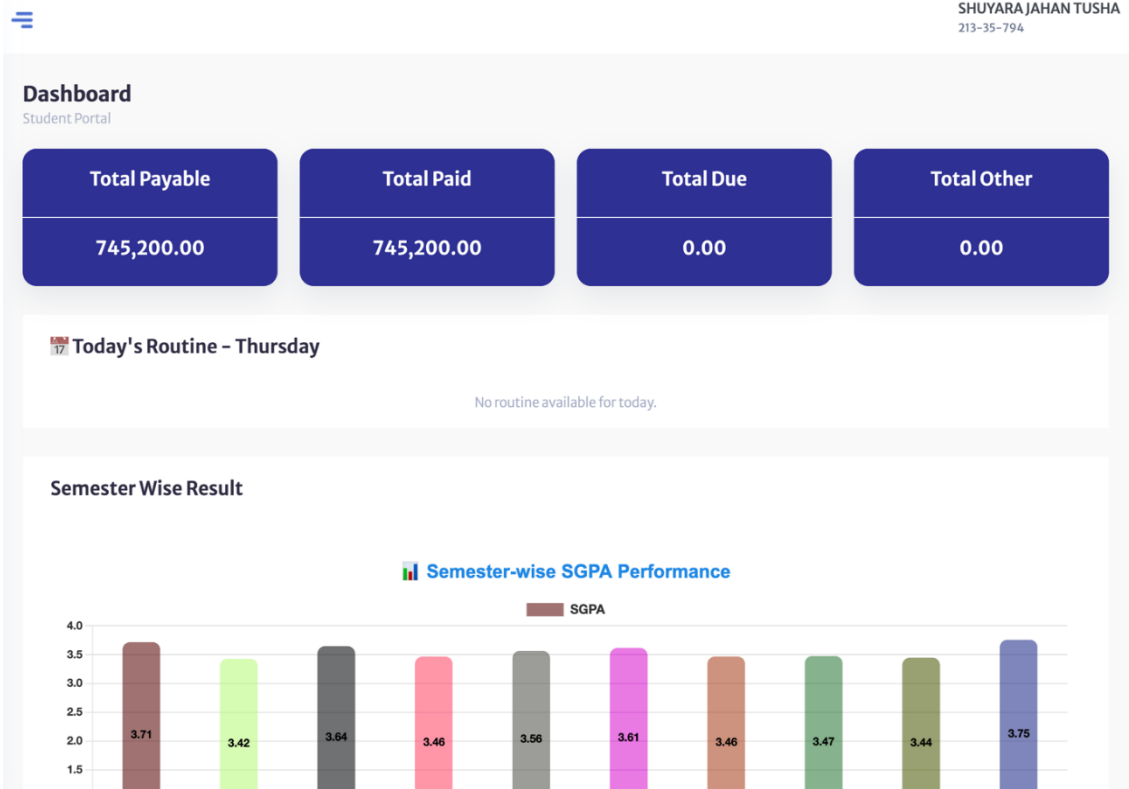
Lastly, the hybrid PLS-SEM and ANN method was a thorough analysis, but future studies would consider other more sophisticated modelling methods to further confirm the findings and also determine other relations. This would help in the continued emanation of strong research models regarding technology adoption behaviour prediction.

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