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TOWARDS A CONCEPTUAL MODEL FOR AI ADOPTION IN MEDICAL LIBRARIES: INTEGRATING TOE, DOI, COM-B, AND UTAUT MODEL

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Abstract:

Artificial intelligence (AI) is transforming library operations through automation and enhanced efficiency, yet its adoption in medical libraries, particularly in Malaysia, remains insufficiently studied. The objective of this study is to propose a comprehensive conceptual framework to explain AI adoption in medical library settings by integrating the COM-B Model, the Technology–Organization–Environment (TOE) framework, and Diffusion of Innovation (DOI) theory. The framework highlights three determinant categories: capability, opportunity and motivation. These factors are proposed to influence intention, which in turn drives adoption behavior. Developed through a narrative literature review and theory synthesis, the framework addresses the limitations of single-theory approaches and offers both theoretical and practical contributions. It provides guidance for medical library administrators and policymakers to enhance AI readiness and establishes a foundation for future empirical research in healthcare education contexts.

Keywords:

Artificial Intelligence, Behaviour, Capability, Conceptual, Opportunity, Motivation

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Introduction

Artificial Intelligence (AI) has become one of the most transformative technologies in libraries, reshaping how information services are delivered. Around the world, AI is increasingly used in key library functions such as cataloguing, information retrieval, user assistance, and knowledge management. Automated cataloguing systems have helped reduce manual work and improve the accuracy of bibliographic records (Bisht et al., 2023), while AI-powered chatbots like ChatGPT are now used for real-time virtual assistance (Vrindha & Syamili, 2025; Zhao & Zhang, 2023). AI has also enabled personalized services through machine learning, allowing libraries to anticipate user needs and recommend relevant resources (Wan, 2024).

Despite these advantages, not all librarians are able to integrate AI into their daily tasks due to limited training and lack of technical skills. Studies show that insufficient instruction and support can hinder the ability of librarians to adopt and use AI tools effectively (Tanuri et al., 2025). Research also demonstrates that AI improves efficiency, reduces operational costs, and increases user satisfaction (Rahmani, 2023; Praveenraj, Agarwal & Singh, 2025; Adeyemi & Muhammed Jamiu, 2025; Yang, 2024; Wagwu et al., 2024). By automating a routine administrative work, AI allows librarians to focus on higher-level responsibilities such as research support, training, and community engagement (Tai & Ghosh, 2025; Sultana et al., 2025). This highlights that AI strengthens the role of librarians rather than replacing them.

However, AI adoption across libraries remains uneven, especially in developing countries where technological infrastructure, policy support, and funding may be limited (Ndela Marone & Mbengue, 2025). Institutional support plays a very important key role in successful implementation, particularly in areas such as financial investment and strategic planning (Tanuri et al., 2025). In Malaysia, recent studies indicate that librarians are motivated to adopt AI because of positive trends, peer influence, and improved work outcomes (Lakulu et al., 2025; Aman & Zakaria, 2024). Yet, it is still unclear whether librarians will continue to adopt AI if their organizations cannot invest in the latest technologies. Therefore, this study aims to examine the factors influencing AI adoption among librarians, focusing on their capability, opportunity, and motivation to use AI in their work.

Literature Review

AI Integration in Library Operations

Artificial Intelligence (AI) is reshaping library operations by transforming traditional practice (Echedom & Okuanghae, 2021; Sofyani & Ayu, 2024) into smarter, more adaptive services. Libraries increasingly deploy AI to automate routine tasks, personalize services, support research, and manage vast volumes of data, thereby enhancing efficiency, accessibility, and user engagement (Pence, 2022; Tai & Ghosh, 2025). Repetitive functions such as circulation, cataloguing, and book sorting are now handled by intelligent systems, reducing manual workload and enabling librarians to focus on higher-level responsibilities such as research support, information literacy training, and user engagement (Georgieva & Georgiev, 2025; Lalitha et al., 2024). Robotics and expert systems further contribute to efficiency in tasks such as shelf reading and book retrieval (Basak et al., 2024; Pence, 2022).

One of AI's most significant contributions lies in improving information retrieval. Natural Language Processing (NLP), semantic search, and machine learning–based retrieval systems allow users to conduct intuitive, context-aware searches that deliver more relevant results than traditional keyword-based methods (Li & Wang, 2021; Adewojo & Dunmade, 2024). These

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advanced discovery tools support researchers by providing efficient access to scholarly materials (Basak et al., 2024). Chatbots and virtual assistants also play an important role in real-time query support, reducing wait times for reference services and improving overall user satisfaction (Tai & Ghosh, 2025; Lalitha et al., 2024).

AI supports highly personalized library services. Machine learning models analyze user behavior, borrowing patterns, and search histories to deliver tailored content recommendations (Adewojo & Dunmade, 2024; Georgieva & Georgiev, 2025). Similarly, predictive analytics aid evidence-based collection development by anticipating demand and guiding acquisition strategies (Ajakaye, 2024). Automated classification, indexing, and metadata generation enhance accuracy, minimize manual effort, and provide valuable insights for institutional decision-making (Bisht et al., 2023; Georgieva & Georgiev, 2025).

Research Gaps

Therefore, a lack of a comprehensive framework study outlining the factors influencing AI adoption among medical librarians, combining the needs of capability, opportunity, and motivation for the librarian to collaborate effectively with AI to enhance library operation and user experiences. Hence, this study proposes a comprehensive conceptual framework that integrates four well-established models: The Technology-Organization-Environment (TOE) framework, the Diffusion of Innovation (DOI), the COM-B model (Capability, Opportunity, Motivation, Behaviour), and the Unified Theory of Acceptance and Use of Technology (UTAUT). By combining these perspectives, the framework aims to capture a multidimensional view of the factors driving or hindering AI adoption, encompassing technological, organizational, environmental, behavioral, and human-centric aspects. This integration addresses the limitations of single-theory approaches and offers a more holistic understanding of adoption behavior. The study not only seeks to fill theoretical gaps in the literature but also offers practical insights for medical library administrators and policymakers. Moreover, previous studies often neglect organizational and human factors, as shown in Table 1.

Table 1: Theories and Models on Technology & AI Adoption

Theory / Model	Key Determinant	Findings	Author & Year
Technology-Organization-Environment (TOE) Framework:	- Key determinants include relative advantage, compatibility, top management support, organizational readiness, and government regulatory support. In public organizations, technological and organizational factors are more critical than environmental factors	Widely used to understand AI adoption at the organizational level, focusing on technological, organizational, and environmental factors.	AlSheibani et al. (2020) ; Horani et al. (2025), Shahzadi et al (2024), AlSheibani, Cheung & Messonm (2018), Yang , Blount & Amrollahi, (2024), Neumann, Guirguis & Steiner (2024)

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Diffusion of Innovation (DOI) Theory:	Innovation characteristics (relative advantage, compatibility, complexity, trialability, observability) - Adopter categories (innovators, early adopters, majority, laggards)	DOI's strength in classifying adopter behavior, but also its weakness in explaining external, organizational, and environmental factors, hence the call for integrated models.	Lund et al (2020), Lund, (2025), Harisanty et al. (2025).
Technology Acceptance Model (TAM) (Davis, 1989)	- Perceived Ease of Use (PEOU) - Perceived Usefulness (PU)	PU and PEOU strongly influence attitudes toward AI adoption. In some contexts, PEOU shows minimal impact. Focus of motivation and individual-centric, but overlooks external factors like organizational support and subjective norms.	Davis (1989); Hussain & Khan (2025); Malatji, van Eck & Zuva (2020); Chang & Huang (2015); Chu & Chen (2016); Turan & Koc (2022); Hartl, Nawrath & Hess (2018); Chatterjee et al. (2021); Wang et al. (2010)
Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1960)	- Attitude toward behavior - Behavioral intention (motivation to engage in behavior)	Useful in predicting intentions behind technology adoption. Lacks explanation of deeper cognitive processes. Does not adequately account for external/environmental influences such as user skills or institutional context, leading to incomplete predictions.	Ajzen & Fishbein (1960); Al-Bukhrani et al. (2025); Kwon, Bae & Shin (2020); Zhikun & Fungfai (2009); Fishbein (2008)
Task Technology Fit (TTF)	- Task characteristics - Technology characteristics	Significant in explaining faculty members' intention to adopt AI in medical institutions. Found insignificant in influencing librarians' AI adoption in Malaysian academic libraries.	Abdekhoda & Afsenah (2024); Aman & Zakaria (2024); Chen et al. (2023); Parthiban & Adil (2023); Etim (2020); Abdekhoda & Dehnad (2024); Gangwar, Date &

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		Criticized for overlooking behavioral and psychological aspects (e.g., trust, fear of job loss). Focused mainly on end-user fit without integrating organizational/human factors. Needs to be combined with other models for stronger explanatory power.	Raoot (2014); Zheng et al. (2024); Simoes, Barros & Soares (2018); Chatterjee et al. (2021)
Unified Theory of Acceptance and Use of Technology (UTAUT)	Performance Expectancy Effort Expectancy Social Influence Facilitating Condition	Considered as one of the most cutting-edge and effective models UTAUT is a viable integrated theoretical framework that, when properly designed and executed within a study, and lends itself to robust statistical analyses such as SEM	Andrew, Ward & Yoon, (2021), Chen, Fan & Azam (2024), Williams et al (2011)

Without adequate training, infrastructural support, and user engagement, AI implementation risks inefficiencies and librarian disengagement (Zondi, 2024; Dei Patris et al., 2025). Yet, the issues of transparency, algorithmic bias, and interpretability are frequently overlooked, raising ethical concerns about reliability and equitable access. Financial constraints, ongoing maintenance costs, and fears of staff displacement further complicate adoption, especially in low-resource environments (Lalitha et al., 2024; Chelmulwo & Sorirei, 2021).

Taken together, the literature highlights AI's transformative potential across library operations automation, personalization, information retrieval, and immersive learning. In medical libraries, these innovations promise to enhance evidence-based information delivery and specialized knowledge management. There is a notable lack of empirical research examining librarian behaviour; the majority of studies privilege technological features over contextual readiness, organizational support, and user capability. Addressing these gaps requires an integrated focus on capability building, institutional readiness, and motivational factors that shape adoption and continued use. Furthermore, the framework sets a foundation for empirical research using quantitative methods to validate proposed relationships and compare adoption patterns across library types and institutional contexts. Through this approach, the study contributes to the broader discourse on digital transformation in the library and information science domain, particularly within the Malaysian healthcare education system.

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Theoretical Framework

TOE Model

The Technology-Organization-Environment (TOE) framework, proposed by Tornatzky and Fleischer (1990), identifies three interrelated contexts that influence the adoption of technological innovations: the technological context, the organizational context, and the environmental context. As a comprehensive model, it provides a flexible analytical lens for examining both internal and external factors that shape organizational decisions regarding technology adoption, including Artificial Intelligence (AI) in medical libraries. Sousa (2023, 2024) highlighted that the TOE framework is among the most widely applied theoretical models in the field of innovation and has proven practical in explaining the process of AI adoption at the organizational level. Building on this, Smit et al. (2024) and Satyro et al. (2024) emphasized that AI adoption must be understood within the organizational setting, as previous studies have consistently underscored challenges such as limited top management support, high implementation costs, inadequate infrastructure funding, and insufficient training, all of which serve as barriers to adoption. Furthermore, organizational and environmental readiness remain critical dimensions. For instance, Badghish and Soomro (2024) underscored the role of relative advantage and compatibility within organizations in facilitating AI adoption in library contexts, reinforcing the idea that both structural preparedness and external pressures significantly affect innovation outcomes.

COM-B Model

The Capability, Opportunity, and Motivation–Behavior (COM-B) model, developed by Michie et al. (2011), is a comprehensive behavioral framework that has been widely applied in analyzing human behavior and designing interventions. It posits that behavior is a function of three interacting components: capability, opportunity, and motivation. This framework has proven successful in health psychology and behavioral sciences, providing insights into contexts such as healthy eating (Isbanner et al., 2024), physical activity engagement (Howlett, Schulz, & Trivedi, 2019), medication adherence (Jackson et al., 2014), young adult eating behaviors (Willmott, Pang, & Rundle-Thiele, 2021), and more recently, the role of socially assistive robots among older adults (Luo et al., 2024). Despite its broad application across diverse domains, the COM-B model has yet to be systematically applied to the study of behavioral intention toward AI adoption in medical libraries.

The strength of the COM-B model lies in its flexibility and strong theoretical grounding, making it applicable beyond health psychology to organizational, behavioral, and technological adoption research. Within the model, capability refers to the psychological and physical capacity of an individual to engage in a behavior, encompassing knowledge, skills, attention, decision-making processes, and behavioral regulation. Opportunity reflects the external factors that enable or prompt behavior, including environmental resources, social support, and institutional structures. Motivation encompasses the cognitive and emotional processes that influence decision-making, such as beliefs, intentions, and habitual responses (Michie et al., 2011).

Furthermore, the COM-B model is integrated into the Behavioral Change Wheel (BCW), a systematic approach to designing interventions. According to Murphy et al. (2023), the BCW provides a step-by-step process for implementation: identifying the core problem, selecting and specifying the target behavior, determining what needs to change, identifying potential intervention functions, and aligning these with policy measures to ensure sustainability. This

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process-driven approach makes the COM-B model not only descriptive but also prescriptive, offering a pathway for designing interventions to address real-world challenges. Applying COM-B to AI adoption among medical librarians could therefore reveal key behavioral determinants and guide the development of targeted strategies to enhance acceptance and utilization of AI in medical library services.

UTAUT Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a widely applied model in technology adoption research, particularly in understanding how individuals accept and utilize new technologies. The model posits four core determinants of behavioral intention and use: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh, Morris, Davis, & Davis, 2003). Performance expectancy, which refers to the degree to which an individual believes that using a particular technology will enhance their job performance, has consistently emerged as a strong predictor of adoption, including in the context of artificial intelligence (AI). Recent empirical studies confirm this finding, indicating that individuals are more likely to adopt AI when they perceive it as useful and capable of improving task efficiency (Kadim et al., 2024; Sánchez & Arcila, 2024; Elyakim, 2025; Emon et al., 2025; Prameka et al., 2024). This construct is conceptually aligned with perceived usefulness from the Technology Acceptance Model (TAM), reinforcing the argument that expectations of performance improvement remain a decisive factor in shaping adoption behavior. In contrast, effort expectancy, which relates to the perceived ease of using technology, has produced mixed results in AI adoption research. While it is often theorized to play a significant role in shaping user intention, evidence suggests that its influence is not always robust. For instance, Prameka et al. (2024) and Ouzif et al. (2025) found that effort expectancy did not significantly predict AI adoption among Moroccan university teachers, suggesting that the perceived ease of use may be less critical in contexts where users prioritize functionality or institutional requirements over usability. Social influence and facilitating conditions, however, have demonstrated significant impacts on AI adoption across multiple contexts. Social influence, defined as the extent to which individuals perceive that important others believe they should use a technology, has been shown to shape user intention through peer expectations and societal norms (Kadim et al., 2024; Elyakim, 2025; Emon et al., 2025). Facilitating conditions, which refer to the availability of organizational and technical resources necessary for system use, also play a pivotal role in determining actual usage behavior. Empirical evidence highlights that sufficient financial support, IT infrastructure, manpower, and technical assistance reduce barriers, enhance capacity, and improve the feasibility of AI adoption. For example, Priandito et al. (2024) emphasized the critical role of infrastructure support in successful AI implementation, while Azab and Elsherif (2025) demonstrated that access to technological resources and external support from NGOs enabled the empowerment of women entrepreneurs in Egypt. Collectively, these findings underscore that adoption is not solely a matter of individual perceptions but is also contingent upon environmental and resource-related conditions that facilitate or constrain technology use.

Conceptual Framework

The proposed conceptual framework is grounded in the integration of four well-established theories: the COM-B model, the Technology - Organization - Environment (TOE) framework, Unified Theory of Acceptance and Use of Technology (UTAUT), and Diffusion of Innovation (DOI). These theories offer a holistic view of the factors affecting AI adoption behavior by considering not only individual user-level variables but also organizational and environmental determinants. The COM-B model emphasizes that behavior, in this case, AI adoption, results

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from the interaction of Capability, Opportunity, and Motivation. Each of these components is expanded using constructs from TOE, UTAUT, and DOI, ensuring theoretical depth and contextual relevance. This framework is tailored specifically to medical librarians in Malaysia, recognizing the unique challenges and professional environments they navigate.

Capability Factor

Capability refers to the individual and organizational capacity to adopt and effectively use AI technologies. It encompasses the skills, knowledge (Michie et al. 2011), and resources (Mikalef & Gupta, 2021) that librarians and institutions must possess to integrate AI into their workflows. At the individual level, this includes digital literacy, technical expertise, and confidence in using AI systems. At the organizational level, capability involves technology readiness, system compatibility, and the ability to adapt existing infrastructure to support innovation. Without adequate capability, even motivated staff or supportive environments may fail to translate into successful adoption.

Capabilities in Technological Context

Technology readiness is crucial for the successful adoption of Artificial Intelligence (AI) across various sectors. These capabilities refer to the inherent function, strength, and potential applications of AI technologies such as data processing, predictive analytics, natural language processing, automation, and decision-making support. It includes the availability of technical infrastructure, the preparedness of human resources, and the level of digital literacy among medical librarians (Bui, Phan & Nguyen, 2024). For AI to be effectively adopted, organizations must evaluate whether these technological competencies align with their operational goals, service delivery models, and sector-specific demands. The organizations need to assess whether AI is able to meet their demand and needs (Pathak & Bansal, 2025; 2024). A library that is technologically prepared is more likely to support AI implementation effectively, from initial procurement to day-to-day usage. Given the complexity of medical information and the growing demand for evidence-based resources, AI has the potential to significantly enhance service quality. However, without sufficient readiness, such as reliable systems, adequate staff training, and appropriate budget allocation, AI cannot be fully or effectively utilized. Therefore, technology readiness emerges as a prerequisite for successful AI adoption in medical libraries

Capability in Organizational Context

In the context of organizational decision making, compatibility is often linked to core capabilities. Compatibility, which refers to the extent to which AI applications align with existing workflows, professional routines, and organizational values (Chatterjee et al., 2021; Nguyen, Le & Vu, 2022). The organization integrates new technologies effectively without disrupting existing systems (Wong & Ngai, 2025; Arroyabe et al. 2024). This concept is closely associated with the Diffusion of Innovation (DOI) theory (Rogers, 2003), which identifies compatibility as a key innovation characteristic influencing adoption rate. Jaklic, Grubljesic, and Popovic, (2018) underscored that compatibility ensure resources and organizational goals align well, facilitating better decision-making outcomes. In practical terms, medical librarians are more likely to adopt AI tools that integrate smoothly with current library management systems, cataloguing standards, and information retrieval processes. For example, an AI tool designed for literature summarization will be more readily adopted if it can be embedded within existing discovery platforms or integrated into the librarians' information literacy instruction practices. Moreover, compatibility reduces the cognitive and operational burden often associated with technological change.

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Capability in Environmental Context

From an environmental perspective, competitive pressure plays a significant role in influencing the adoption of artificial intelligence (AI) technologies within medical libraries (Tornatzky & Fleischer, 1990). Defined as the degree to which external institutional forces compel organizations to adopt innovations, competitive pressure stems from the need to remain relevant and responsive in a rapidly evolving technological landscape (DiMaggio & Powell, 1983; Makridakis, 2017). The environment encompasses external factors such as industry trends, peer institution practices, user expectations, and regulatory requirements, all of which contribute to shaping organizational behavior regarding technology adoption (Tornatzky & Fleischer, 1990). For example, studies reported that competitive pressure is not always a primary factor. Studies by Guo and Rigamonti (2022) acknowledged that competitive pressure is not a primary factor and less impactful for AI adoption in libraries compared to other factors, but this pressure is important in the medical library's context as competitive pressure manifests in several forms.

First, there is the growing expectation from healthcare professionals, medical students, and academic stakeholders for faster, more accurate, and AI-enhanced information services (Urquhart & Turner, 2016). Competing libraries or institutions that have successfully integrated AI, such as through automated literature screening, AI chatbots, or intelligent search tools, set new service benchmarks that other libraries feel compelled to meet (DiMaggio & Powell, 1983). This external benchmarking effect intensifies the perceived need for innovation to avoid falling behind in-service quality and operational efficiency. Hence, competitive pressure plays a significant role in shaping the environmental strategies of AI adoption in medical libraries.

Second, the wider trend to digitalization in higher education and healthcare also seems to have increased institutional awareness of the strategic importance of AI (Bates et al., 2020; Pelletier et al., 2022). Once considered a secondary service, medical libraries are facing increased demands to justify their existence in the new digital age of the institute or college to which they belong by implementing state-of-the-art technologies (Oakleaf, 2010). This casts top-down pressure on library leadership to invest into AI to remain competitive institutionally, in terms of their accreditation standards, and to keep their stakeholders happy (Mezias et al., 2002). Moreover, innovation-centric performance indicators are gaining ground as focus indicators for funding bodies and policymakers (Etzkowitz & Leydesdorff, 2000). Libraries that resist adopting AI may risk losing relevance in the national and regional knowledge infrastructure, especially when surrounded by institutions that embrace digital innovation. As a result, competitive pressure acts as both a motivating force and a contextual constraint, prompting medical libraries to proactively explore, evaluate, and integrate AI tools as part of their strategic development (Zhu et al., 2006). The competitive pressure, as an environmental factor, does not merely encourage technology adoption; it also reshapes organizational priorities, influences leadership decisions, and accelerates institutional readiness for digital change (Oliver, 1991). When effectively harnessed, this pressure can catalyse transformation, positioning medical libraries at the forefront of innovation in health information management (Christensen, 1997).

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Opportunity Factors

Opportunity in a Technological Context

The perceived financial cost of implementing artificial intelligence (AI) is widely recognized as a significant opportunity-related determinant in technology adoption across institutional settings. Meaning to say, organizations that have resources like funds for infrastructure, software, hardware, training, and maintenance costs have a bigger chance to adopt AI (Mikalef et al. 2021). A primary area of concern lies in the initial capital investment required for AI adoption. According to Singh and Nayyar (2024), the expenditures are involved in high-performance computing infrastructure and specialized software tailored for information retrieval, classification, and user engagement tasks. AI technologies applicable to medical libraries, such as intelligent search engines and databases, automated metadata generation tools, and virtual reference systems, require not only robust technical systems but also integration with existing library management software. Not only that, but continuous maintenance and upgrades are needed to ensure the AI system remains effective and up-to-date. According to Singh and Nayyar (2024), such initial outlays can be substantial, particularly in resource-constrained institutions such as publicly funded hospital libraries or academic health centers.

There is a significant financial commitment required for training personnel; hence, building further compounds the financial burden. AI implementation necessitates the upskilling of library personnel, especially in areas such as data analytics, AI-assisted knowledge discovery, and digital curation. Abioye et al. (2021) underscore the high costs associated with both initial training and ongoing professional development, especially given the fast-evolving nature of AI technologies. Studies by Huang (2024) and Barsha & Munshi (2023) revealed that funding and the cost of AI implementation are relatively high. For medical libraries, this implies continued investment in workforce development to maintain the competency of the library staff in applying AI to complex biomedical information environments.

Operational costs related to data governance, system maintenance, and compliance are also non-trivial. The management of sensitive clinical and research data, often stored or processed through AI-enhanced platforms, requires adherence to strict privacy and ethical regulations. Singh, Arora, and Singh (2025) highlight that regulatory compliance can necessitate additional financial commitments for cybersecurity infrastructure, audits, and certifications. In medical libraries, particularly those embedded in hospital systems, this represents a critical consideration due to the high stakes associated with health data protection. Despite these financial challenges, AI adoption presents significant strategic advantages. When implemented effectively, AI can lead to long-term cost optimization and improved service delivery. As noted by Bhatnagar and Sehajpal (2024), AI-driven automation and decision-support capabilities can reduce routine workload, streamline information services, and enhance resource utilization. In the medical library context, these benefits may manifest through faster information retrieval for clinicians and researchers, more personalized user services, and reduced administrative overhead.

Moreover, the potential for a positive return on investment (ROI) is increasingly supported by empirical findings. Li and Huang (2024) suggest that, when aligned with institutional digital transformation goals, AI adoption can generate financial gains through increased operational efficiency and improved user outcomes. For medical libraries, this alignment may be realized

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through enhanced research support, integration with hospital information systems, and contribution to evidence-based clinical practice.

Opportunity in Organizational Context

Top management support is consistently identified as a critical factor and enabler in successful adoption and implementation (Korzynski et al., 2024; Wael AlKhatib, 2023; Ghani, Ariffin & Sukmadilaga, 2022). This support encompasses leadership endorsement, strategic resource allocation, and articulation of a long-term vision, which is essential in shaping an environment conducive to technological innovation. Previous studies reveal that top management support significantly predicts AI adoption intention (Hmoud, 2021; Panda & Mahantshetti, 2023; Ghani, Ariffin & Sukmadila, 2022; Bin-Nashwan & Li, 2025). Effective leadership can help overcome internal resistance to change by promoting trust, reducing uncertainty, and encouraging stakeholders to engage with new technologies (Nizar et al. 2025). Furthermore, endorsement from leadership aligns AI initiatives with organizational mission and values, thereby embedding innovation within the strategic fabric of the institution (Sharma & Gupta, 2025). Effective resource allocation by top management is a critical determinant of successful AI implementation, as it ensures the availability of essential financial, human, and technological resources. Strategic investment in AI readiness, particularly in infrastructure, workforce development, and capacity building, enables organizations to build a robust foundation for the adoption and integration of AI technologies. This includes funding for specialized training programs, recruitment of skilled personnel, and the continuous development of digital competencies necessary for navigating AI systems (Bin-Nashwan & Li, 2025; Fetais et al., 2022; Khan, Emon, & Nath, 2024). Moreover, judicious resource allocation plays a key role in mitigating common implementation challenges, such as workforce skill deficits and data security vulnerabilities, both of which can significantly hinder the scalability and sustainability of AI initiatives (Sharma & Gupta, 2025). By proactively addressing these barriers, top management not only facilitates smoother adoption but also reinforces organizational resilience and technological competitiveness.

Opportunity in Environmental Context

The successful adoption of such complex technologies hinges not only on individual or organizational willingness but also on the availability of supportive environmental and infrastructural elements. One of the most pivotal determinants in this context is facilitating conditions, a construct drawn from the Unified Theory of Acceptance and Use of Technology (UTAUT). As AI tools demand significant shifts in digital capability, policy alignment, and user preparedness, understanding how facilitating conditions influence AI adoption is essential, particularly in resource-sensitive environments such as small and medium-sized enterprises (SMEs) and public institutions like libraries.

In the UTAUT framework, facilitating conditions are defined as “the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003). These conditions encompass technical infrastructure, training programs, user support mechanisms, and institutional policies that collectively reduce the effort required for technology implementation (Dwivedi et al., 2019). Facilitating conditions go beyond mere access to tools; they also involve structured support mechanisms that ensure users are equipped and confident in engaging with emerging technologies. This concept is crucial in understanding how organizations can successfully integrate AI into their operations, with the existing opportunities that facilitate the process of AI adoption. Mosnunola et al. (2018) argue that facilitating conditions act as a foundational pillar in the successful

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integration of new technologies, especially when those technologies disrupt existing workflows and require new competencies. In this light, facilitating conditions serve as both a buffer against resistance and a driver for sustained adoption.

In the context of AI adoption in medical libraries, facilitating conditions play a particularly critical role due to the complexity and perceived risk associated with AI technologies. As AI often requires changes to core operational practices, organizations must ensure that users have not only the technical tools but also ongoing institutional backing. According to Zavodna, Uberwimmer, and Frankus (2024), one of the major barriers to AI implementation in SMEs is the lack of facilitating conditions, namely, insufficient technical support, inadequate infrastructure, and unclear regulatory guidance. Their pilot study further reveals that without these enablers, even organizations with positive attitudes toward AI may fail to progress toward actual implementation. Moreover, other frequently cited barriers, such as skill shortages, AI-related anxiety, and ethical ambiguities, are often exacerbated by weak facilitating conditions (Makridakis, 2017; Dwivedi et al., 2021). These findings emphasize that facilitating conditions are not merely passive enablers but active determinants that shape users' ability and willingness to adopt AI. Importantly, the presence of robust support systems can also mediate the negative impact of fear and uncertainty associated with AI, particularly in public service sectors such as education, libraries, and healthcare, where user readiness and institutional capacity vary greatly.

Motivation Factors

Motivation can be defined as the desire and determination that drive an individual to accomplish tasks and to achieve goals (Bandhu et al. 2024). Motivation is categorized into two types: intrinsic and extrinsic. This study will investigate motivation to adopt AI among medical librarians using the technological, organizational, and environmental context.

Motivation in Technological Context

Motivation is a crucial driver of behavioral change, particularly in the adoption of new technologies. Within the technological dimension, intrinsic motivation can be understood as factors that enhance enthusiasm for work and improve job performance (Hassan & Becker, 2025). This closely aligns with the concept of perceived usefulness introduced by Davis (1989) through the Technology Acceptance Model (TAM). In the medical library context, librarians' motivation to adopt AI largely stems from its perceived usefulness in improving efficiency and productivity. AI can streamline operations, automate repetitive tasks, and allow librarians to focus on more complex, value-added services (Hussain & Khan, 2025; Jha, 2023). Empirical evidence further supports this view. For example, Gyesi, Amponsah, and Ankamah (2025) found that perceived usefulness had a stronger influence on medical librarians' behavioral intention to adopt AI than perceived ease of use, highlighting its central role in shaping adoption decisions.

Beyond efficiency, motivation is also fuelled by curiosity, experimentation, and the pursuit of innovation. Gupta and Gupta (2023) emphasized that librarians' willingness to explore emerging tools stems from their interest in learning and experimenting with AI technologies. Similarly, Okunlaya, Syed Abdullah, and Alias (2022) noted that the strategic relevance of AI, along with its innovation potential, motivates librarians to remain competitive and relevant in the digital era. In summary, perceived usefulness is the most critical technological motivator for AI adoption in medical libraries. By demonstrating clear benefits in improving performance, efficiency, and professional relevance, perceived usefulness not only strengthens

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librarians' intention to adopt AI but also sustains their motivation to engage with technological change.

Motivation in Organizational Context

In the organizational context, trust serves as a vital motivational driver that directly influences employees' willingness to adopt new technologies and improves the chances of successful AI integration (Copper et al., 2025; Aziki, Ourrani, & Faili, 2024). Within medical libraries, this trust relates to the assurance that AI systems are reliable, secure, and consistent with professional and institutional values. Librarians, for example, must have confidence in how AI handles sensitive user data, automates workflows, and supports decision-making in critical areas of library services (Choudhury & Shamszare, 2023; Hasan et al., 2023). However, a persistent challenge is the lack of transparency in AI technologies. Studies by Salloum (2024) and deZoeten, Ernst, and Rothloauf (2023) emphasize that the "black-box" nature of AI can undermine confidence, limiting librarians' motivation to integrate these tools despite their technical capabilities. This highlights that technological advancement alone is insufficient—trust is the key determinant of adoption.

From an organizational motivation perspective, trust functions as a psychological enabler that reduces fear and enhances employee commitment. Institutions that establish clear policies on ethical AI practices, data privacy, and accountability create an environment where librarians feel safe experimenting with new tools and systems (Omrani et al., 2022; deZoeten et al., 2023). Institutional support not only minimizes perceived risks but also strengthens intrinsic motivation, as librarians feel that they are backed by their organizations in exploring innovative solutions. Radhakrishnan and Chattopadhyay (2020) reinforce this perspective, showing that trust—alongside organizational factors such as technical competency, management support, incentives, and security policies significantly influences the adoption of AI. Thus, trust operates not merely at an individual level but as an organizational resource that aligns staff behavior with institutional strategies.

Ultimately, trust is both a cultural and structural asset within organizations, shaping how employees perceive and engage with technological change. When librarians believe that their institutions have a strategic vision for AI, supported by continuous training and transparent communication, their confidence in these systems grows, increasing their motivation to adopt them. In this way, trust bridges institutional assurance and individual readiness, creating a climate of safety, competence, and shared responsibility. Positioned within this conceptual framework, trust emerges as a core motivational construct that ensures librarians are not only willing but also prepared to embrace AI. This is essential for driving sustainable technological change in knowledge-based organizations such as medical libraries, where trust underpins the balance between innovation and professional responsibility.

Motivation in Environmental Context

Behaviour can be shaped through motivation. Whether through internal or external factors, it normally acts as a driver that influences our actions and choices. It either forces us towards positive or negative behavioural changes (Bandhu et al. 2024). In addition, human behavior can also be influenced by social, cultural, and environmental factors. Social influence can be found in the UTAUT framework, is a primary predictor of behavioral intention to adopt AI alongside trust and facilitating conditions (Chen, Fan & Azam). According to Aman and Zakaria (2024), peer and colleague behaviour is a major driver of AI adoption in a workplace. Hence, in this study, social influence will be classified as external motivation that directly or

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indirectly drives librarians to adopt AI in medical libraries. According to Dashen and Noa (2024), the adoption of AI in the workplace should be accompanied by hedonic motivation and positive emotion towards AI. It is also suggested a peer encouragement enhances librarians' willingness to learn and adopt AI technologies. Similar studies reported that the librarian's intention to adopt AI is positively influenced by social factors and highlighted the importance of support from peer and professional networks in fostering AI adoption (Aman & Zakaria, 2024; Gupta, 2025; Chen, Fan & Azam, 2024 & Khan, 2020). All these factors are proposed to directly influence the intention to adopt AI, which then leads to actual adoption behavior as shown in Figure 1.

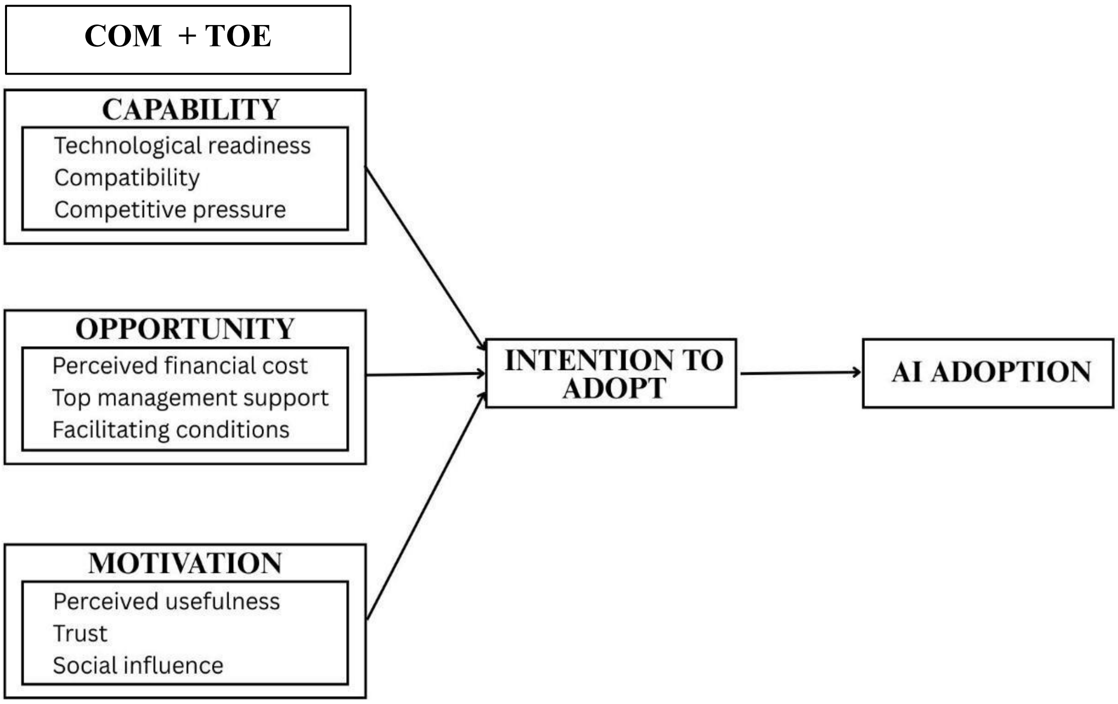

Figure 1: Proposed Conceptual Framework

Methodology

This conceptual framework provides the foundation for empirical validation through a quantitative research design. A COM-B model is rarely adopted in quantitative studies, and the interview method is commonly used in implementing this model. There is a lack of studies using the COM-B model, and it's not statistically tested, especially in AI adoption within this context. Yet, quantitative approach is deemed appropriate given the scarcity of studies on AI adoption within the medical library context, where evidence remains largely anecdotal and lacks statistical validation. To address this gap, the study will employ a structured questionnaire to measure the identified constructs. A 5-point Likert scale, as recommended by Koo and Yang (2025), is adopted due to its suitability for capturing nuanced responses within relatively small populations. The target respondents are medical librarians from both public and private medical institutions in Malaysia, ensuring representation across diverse organizational settings. Data will be analyzed using Structural Equation Modelling (SEM), which allows for simultaneous testing of relationships among constructs while assessing the validity of the proposed model.

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The sampling strategy will employ stratified purposive sampling, selected for its relevance in studying a population with specific characteristics such as medical librarians. Purposive sampling is recognized for its practicality and precision, as it allows researchers to deliberately select participants who are most relevant to the study objectives (Campbell et al., 2020). In addition, stratification ensures adequate representation of subgroups across institutional types, thereby improving the robustness of findings. This method is not only efficient in terms of time and resources but also enhances alignment between the sample and the study objectives (Tangco, 2007). By focusing on a smaller yet well-defined population, the study ensures the collection of high-quality data that is both manageable and directly relevant to the research aims.

Theoretical Contribution*:* The development of a comprehensive and robust model for understanding AI adoption. By uniquely integrating four established theories, the TOE framework, Diffusion of Innovation (DOI), the COM-B Model, and UTAUT, this research offers a multi-faceted framework that overcomes the limitations of single-model approaches. It provides a holistic lens that captures the critical interplay of capability and motivation and studies behavioral intention, which creates a more complete picture of the technological, organizational, and environmental context in place.

Practical Contribution: The model provides invaluable, evidence-based insights for library administrators, policymakers, and institutional leaders. It acts as a clear roadmap, identifying the specific drivers that influence a librarian's intention to adopt AI and empowering decision-makers to create effective strategies. By understanding these key determinants, management can develop targeted action plans, such as implementing specialized AI training programs, strategically allocating budgets, and fostering a supportive culture that encourages technological innovation and readiness.

Limitation

Because this study focuses exclusively on medical librarians in Malaysia, the findings may not be generalizable to librarians in other types of libraries (e.g., academic, public, or special libraries) or to professionals in different countries. Cultural, institutional, technological, and policy environments vary significantly across regions and organizational settings, so the determinants of AI adoption observed in this study may differ elsewhere. A key limitation of the current framework is that, although it effectively integrates constructs from COM-B, TOE, UTAUT, and DOI, several important dimensions remain underdeveloped or implicit. For instance, the theoretical mapping between constructs and their parent theories is not visually or conceptually explicit, which may reduce clarity in interpretation. Additionally, the model treats all predictors as having direct effects on intention without accounting for possible mediators or moderators such as demographics, institutional policies, or contextual factors. The environmental dimension is narrowly represented through competitive pressure, omitting broader influences like government regulations, vendor support, or digital infrastructure.

Conclusion

The study provides a new development of the comprehensive framework that explains the key determinants of AI adoption among medical librarians. By integrating multiple theoretical perspectives, the model offers a robust and adaptable foundation that addresses gaps in existing knowledge and supports future empirical validation. The framework also carries meaningful practical value, equipping library leaders and policymakers with insights to navigate the challenges of digital transformation and strategically implement AI solutions. Beyond its

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theoretical contribution, this research plays an important role in reducing the digital divide within Malaysia's library ecosystem. By promoting AI-enabled innovations, it supports the advancement of healthcare knowledge services and positions medical libraries as proactive partners in the information age.

However, several limitations should be acknowledged. Because the study focuses exclusively on medical librarians in Malaysia, the findings may not be generalizable to other library sectors or to professionals in different countries. Cultural, institutional, technological, and policy environments vary across regions, and these differences may influence AI adoption patterns elsewhere. In addition, although the framework integrates constructs from COM-B, TOE, UTAUT, and DOI, some elements remain conceptually implicit. The mapping between constructs and their parent theories is not visually or explicitly illustrated, which may limit clarity for future researchers. The model also assumes direct effects on adoption intention and does not account for potential mediators or moderators such as demographics, institutional support, or contextual constraints. Furthermore, the environmental dimension is narrowly represented through competitive pressure, omitting broader influences such as government regulation, vendor support, or technological infrastructure.

Future research could address these limitations by testing moderating or mediating effects such as digital literacy, workload, or perceived risk to better explain variation in AI adoption. The environmental and organizational components of the model can be expanded to include policy alignment, resource allocation, technological readiness, innovation culture, or system usability. Differentiating between individual-level and institutional-level adoption would also offer deeper insight, as librarians' personal acceptance may not align with organizational priorities. Finally, studies should go beyond initial adoption and examine post-adoption behaviour, including continuance intention, system success, implementation maturity, and feedback loops that show how sustained AI use strengthens capability, opportunity, and motivation over time.

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