Public Library Quarterly

ISSN: 0161-6846 (Print) 1541-1540 (Online) Journal homepage: www.tandfonline.com/journals/wplq20

AI Experimentation Policy for Libraries: Balancing Innovation and Data Privacy

Varun Gupta

To cite this article: Varun Gupta (2026) AI Experimentation Policy for Libraries: Balancing Innovation and Data Privacy, Public Library Quarterly, 45:1, 9-29, DOI: 10.1080/01616846.2024.2445356

To link to this article: https://doi.org/10.1080/01616846.2024.2445356

Published online: 29 Dec 2024.

Submit your article to this journal

Article views: 3672

View related articles

View Crossmark data

Citing articles: 9 View citing articles

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=wplq20

PUBLIC LIBRARY QUARTERLY
2026, VOL. 45, NO. 1, 9–29
https://doi.org/10.1080/01616846.2024.2445356

Routledge
Taylor & Francis Group

Check for updates

AI Experimentation Policy for Libraries: Balancing Innovation and Data Privacy

Varun Gupta [a,b]

[a]Multidisciplinary Research Centre for Innovations in SMEs (MrciS), Gisma University of Applied Sciences, Potsdam, Germany; [b]Department of Economics and Business Administration, University of Alcala, Alcalá de Henares, Madrid, Spain

ABSTRACT

This paper presents a strategic framework for librarians to ethically experiment with AI technologies, emphasizing data privacy and compliance. Developed through a consulting project, it categorizes library tasks based on frequency and data sharing needs, resulting in four AI experimentation strategies: Proactive Optimization, Controlled Experimentation, Opportunistic Experimentation, and Conservative Approach. Practical examples, like AI-assisted reference services for entrepreneurs, illustrate responsible experimentation without sensitive data sharing. The framework recommends documenting outcomes for evaluations and integrating Monitoring & Evaluation (M&E) to align AI experiments with library objectives, ensuring AI's ethical and effective use in enhancing library services. This article suggests that to enhance the practical implementation of the proposed AI experimentation framework and policy in libraries, it is crucial to help librarians become familiar with identifying sensitive data, converting real data into synthetic data, and understanding the implications of sharing information with commercial large language model (LLM) service providers. It highlights the need for foundational training on data privacy, ethical AI practices, and risk assessment, offering solutions such as checklists, training programs, and knowledge-sharing platforms to empower library professionals.

ARTICLE HISTORY
Received September 2024
Accepted December 2024

KEYWORDS
Academic libraries; AI policy; Artificial Intelligence (AI) technologies; experimentations; Monitoring & Evaluation (M&E); Public libraries

Introduction

Libraries, both academic and public, have become essential resources for businesses, offering a range of support services for instance, market research assistance, business references, entrepreneurship skills development programs, access to market research tools, instruction guides, technology-related programs etc (Gupta 2024a;, 2024b; Gupta and Gupta 2023b; Gupta and Rubalcaba 2022). Through collaboration with other libraries and innovation partners, they enhance their role as vital knowledge hubs for entrepreneurs. Libraries must keep pace with the evolving technological landscape, for instance, Artificial

CONTACT Varun Gupta varun.iit13@gmail.com Multidisciplinary Research Centre for Innovations in SMEs (MrciS), Gisma University of Applied Sciences, Potsdam 14469, Germany

This article has been corrected with minor changes. These changes do not impact the academic content of the article.

© 2024 The Author(s). Published with license by Taylor & Francis Group, LLC.

Intelligence (AI), to innovate their services and provide essential information guides for patrons, enabling them to leverage emerging technologies in their entrepreneurial journeys. This requires libraries to first understand the functional capabilities and limitations of new technologies. Once equipped with this knowledge, they can identify potential use cases relevant to entrepreneurship. These insights can then be referenced and shared with patrons, helping them effectively integrate cutting-edge tools into their business strategies.

To effectively integrate new technologies, librarians are encouraged to engage in systematic incremental and small but continuous experimentations with the technology through two complementary frameworks: Need-Based Experimentation (NBE) and Curiosity-Based Experimentation (CBE) (Gupta and Gupta 2023a, 2023b). NBE focuses on identifying and addressing specific challenges within the library, where librarians experiment with technology solutions to resolve current issues and improve services. In contrast, CBE allows librarians to explore new technologies out of sheer curiosity, driven by a desire to learn and discover potential innovations, even if they don't address immediate needs. Familiarity with technologies enables librarians to effectively address library needs by identifying potential use cases for suitable technologies they've previously experimented with. Through past experimentation, librarians gain insights into the capabilities and limitations of different tools, allowing them to match these technologies to specific challenges within the library.

AI applications are undeniably user-friendly, offering intuitive interfaces that make them accessible to a wide range of users. However, the full potential of these technologies lies in myriads of possible use cases they present. For instance, Generative AI like Chat Generative Pre-Trained Transformer (ChatGPT) produces useful content for the users based on their queries expressed as prompts. However, there are plenty of possible use cases in libraries for this technology, with some more valuable than the others. It is only through systematic experimentation that libraries can uncover the most effective applications of AI, discovering both the scenarios where it enhances operations and those where it may not be the best fit. This exploratory approach allows libraries to maximize the benefits of AI while also identifying its limitations, ensuring that the technology is applied where it can truly add value.

While AI presents opportunities to enhance library services (Ajani et al. 2022; Echedom and Okuonghae 2021; Winkler and Kiszl 2022), technologies like ChatGPT also face limitations, such as inaccuracies, data protection concerns, privacy risks, accessibility issues, biases, and ethical challenges (Fui-Hoon Nah et al. 2023; Nehra and Bansode 2024; Panda, Bhatt, and Satapathy 2024). These limitations may hinder librarians' ability to experiment with AI, either due to resistance or the need for greater resource investment and specialized expertise to carefully test and measure AI's outcomes. One major issue discovered through discussions with librarians was their significant concern over privacy issues and the potential risks associated with sharing

library-sensitive data (Gupta 2024a). Lo (2024b) emphasizes that library staff have a foundational grasp of AI and acknowledge its potential advantages; however, their readiness to implement such technologies is hindered by the necessity for additional training and the development of ethical frameworks. In a similar vein, Kaushal and Yadav (2022) discovered that while stakeholders generally endorse AI tools such as chatbots, they approach these technologies with caution, citing concerns about privacy and uncertainty regarding AI's ability to handle complex tasks effectively.

There is a need for an AI experimentation policy that allows librarians to freely experiment with AI technologies in areas where sensitive data is not involved to identify potential use cases, while enforcing stricter controls for experiments involving sensitive data. Sensitive Data refers to information that must be protected due to its potential to cause harm or privacy violations if disclosed without proper authorization. This includes personally identifiable information (PII), financial details, and other data that, if exposed, could jeopardize an individual's privacy, security, or create negative impacts. For instance, University of Edinburgh defines sensitive data as information that, if disclosed, could cause harm to individuals, organizations, or the institution. It includes personal, financial, or confidential data that requires protection due to privacy, legal, or security concerns. The sensitivity of data is determined by evaluating the potential impact on individuals or the organization if the information were exposed, revealed, or lost, rather than by fixed categories.[1]

Sensitive data in the context of libraries encompasses a broad range of information that, if exposed or misused, could cause harm or violate privacy, security, or legal standards. This includes patron information such as names, contact details, borrowing records, and usage patterns, but also extends to non-patron data, such as internal operational records, intellectual property, unpublished research data, staff information, and institutional strategies. Additionally, sensitive data may include details of library transactions, such as payment information, interlibrary loan records, and digital resource access data. When conducting experiments with Generative AI, mishandling any of this sensitive data – whether related to patrons or internal operations – can have significant implications, risking privacy breaches, data misuse, or damage to institutional reputation.

This article draws on consulting experience with a library that adopted ChatGPT through an incremental experimentation process. The library systematically explored potential use cases, identifying areas where the AI could be effectively integrated, as well as situations that required more carefully designed and rigorous experimentations. These experiments were carefully confined to scenarios where the application did not necessitate sharing library or patron data, ensuring both privacy and security throughout the evaluation process. This article also outlines four strategies that librarians can use to conduct experimentations with AI technologies, which are presented through

a 2×2 matrix tool. This matrix helps librarians select an experimentation strategy by guiding the process based on Library Task Frequency and Data Sharing Necessity *(sensitive data)*. The AI policy for fostering experimentations in the library is also provided.

Monitoring & Evaluation in libraries

Monitoring and Evaluation (M&E) is crucial for libraries conducting AI experimentation, as it enables both formative and summative evaluations of their efforts. Formative evaluations help libraries assess the early stages of AI experimentation, learning from the evaluation insights to further improve the ongoing experimentations. Summative evaluations, on the other hand, assess the overall impact of AI experimentation, such as the long-term effects on entrepreneurs supported by the libraries, based on the use cases implemented. This process allows libraries to measure the effectiveness of their AI applications in business support, research services, and traditional patron services, ensuring they are strengthening their services and meeting the needs of their users. Through this process, libraries can determine which AI applications are most effective, what are the possible use cases (or misuse cases) of the technology, and what are the heights of the possible implementation.

Gupta (2024c) recommends integrating monitoring and evaluation (M&E) with experimentation, as M&E allows for the assessment of experiment effectiveness. This approach enables library managers to leverage past evaluation results to enhance future experimental efforts. Poll and Payne (2006) recommended employing outcome-based evaluations in libraries to demonstrate the impact and value of their services. Literature does provide different methods to conduct library impact and performance evaluation (Urquhart 2018; Yim, Fellows, and Coward 2020). Libraries Build Business (LBB), an initiative by the American Library Association (ALA) supported by Google.org, aimed to enhance libraries' efforts in promoting small business success within their communities. ALA and 13 participating libraries collaborated with Cicero Group, an impact consulting firm, to develop a monitoring and evaluation (M&E) framework and guide libraries in implementing M&E activities. The evaluation results indicated that these library initiatives were timely, relevant, and had a significant positive impact on their communities (American Library Association 2023). Public libraries also contribute to supporting the monitoring and evaluation of programs aimed at achieving the SDGs by offering access to essential information and resources (Aregbesolaa et al. 2024). This means that the concept of M&E is not completely new to libraries, as it is well-documented in the literature and many libraries have been conducting M&E activities. The current focus is on demonstrating the impact of their initiatives and further developing their skills in conducting M&E, as evident from ALA, public library, and Cicero Group.

Consulting project with library

In a recent consulting experience with one of the libraries, the objective of the consulting project was to explore the practical applications of ChatGPT while ensuring that no library or patron data was shared during the experimentation. The consultant (author of this paper) identified that there could be multiple possible use cases of the technology for the reference librarians offering support for the entrepreneurs. This, of course, depends on the range of services offered to the patrons. Much of the librarian's tasks could range from high-frequency tasks (tasks that are undertaken repeatedly, for instance, e-mail drafting, program course designing, teaching guides, reference guide about how to open the business etc) to less-frequency tasks (for instance, customized reference support for the unique business need). Additionally, libraries do hold sensitive information, for instance, patrons' personal information, which cannot be shared with the AI applications (as well as with third parties, for instance, with consultants). The experimentation with the technology requires librarians to have continuous interactions with it and identify possible use cases of the technology. These use cases are then presented to the management for possible approval and implementation across the library. Owing to differences in library task frequency and data sharing involved, the libraries require different experimentation strategies namely, *Proactive optimisations, Controlled Experimentations, Opportunistic Experimentation, and Conservative Approach*. The consulting project resulted in a comprehensive framework, AI experimentation strategy, and controlled experimentation protocols, offering clear direction for the ethical exploration of AI technologies within the library setting.

Framework for conducting AI experimentations: based on consulting project

To experiment with AI technologies, the librarian must first consult the organization's *data classification policy (or existing classifications in place)* to identify which data is classified as sensitive and which one is not. Based on this classification, the librarian can then select an appropriate experimentation strategy from the provided 2×2 framework, depending on the frequency of the library task. The framework provides librarians with four strategies for conducting the AI experimentation to find possible use cases, based on two factors, namely, *Library Task Frequency* and *Data Sharing Necessity (sensitive data only)*. This framework helps librarians determine appropriate strategies for experimenting with AI tools, balancing innovation with data protection. This framework helps librarians to start with highly frequent Library Tasks having no data sharing needs. Then, as librarians have gained good experience

with the technology, the experimentation can continue with highly frequent Library Tasks with the need to share data but in a controlled manner. The adoption of the technology for the possible use cases identified will provide greater value to the libraries. Thereafter, the experimentations can proceed with less frequent Library Tasks with no data sharing requirements if there are opportunities that provides greater business value and finally with those with need for data sharing (if really required).

Library Task Frequency refers to how often a particular task is carried out within the library's operations. High-Frequency Tasks are those performed regularly and consistently as part of library operations for the entrepreneurs. This could involve reference services like how to start a business, teaching guides for courses like systematic literature reviews, and developing business support program invitations and schedules (*without sharing personal information)*. Since these tasks occur often, there is a significant opportunity to leverage AI tools as the librarian is very familiar with the tasks, required improvements, and hence the ability to evaluate the value worth of the technology under experimentation. Low-Frequency Tasks, on contrary, are those that are performed less regularly or sporadically. This could involve customized reference services to meet unique business need. Due to their infrequent nature, these tasks may not justify constant experimentation but can benefit from targeted exploration when specific opportunities arise. For instance, developing specialized content for exporting in times of pandemic, which could be useful for entrepreneur community.

Data Sharing Necessity pertains to the extent to which tasks involve handling or sharing library of their patron-sensitive information with the AI technology under experimentation. Sharing data with ChatGPT can lead to it being used for training the model, potentially exposing sensitive information. This raises privacy concerns, as sensitive data could be inadvertently retained or analyzed, impacting confidentiality. For instance, no sensitive Data Sharing is required to use ChatGPT for improving teaching guides for performing systematic literature survey for the entrepreneurs. Additionally, sensitive data sharing will be required to experiment with the ChatGPT for customized reference services for unique business context or internal library reports. In some organizations, the data is classified into various categories, for instance, Harvard University classifies data as DSL1 (Publicly accessible and unrestricted data), DSL2 (Unpublished nonsensitive research data), DSL3 (sensitive data), DSL4 (sensitive data), and DSL5 (sensitive data) (Harvard University 2024). If this classification already exists in the organization, the librarian can determine which data is classified as sensitive and which is not, in accordance with the organization's policies. Figure 1 shows the four experimentation strategies.

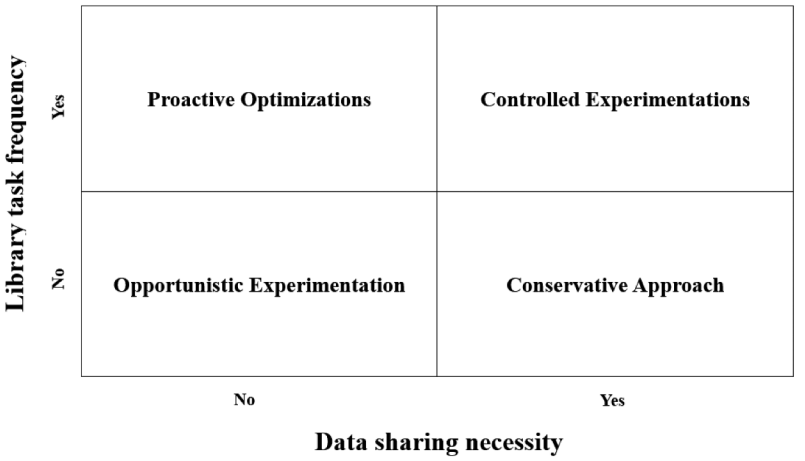

Figure 1. AI experimentation strategies framework matrix.

Proactive optimizations

This strategy focuses on continuous experimentation and improvement for high-frequency library tasks that involve no sensitive data sharing with the AI applications. Since these tasks are performed regularly and do not require handling sensitive information, there is ample opportunity for iterative enhancements and optimization of librarian tasks using AI tools. For instance, in the consulting project, the librarian interacted with the ChatGPT by providing different prompts. After successive promptings, the librarian based on the technology ability to generate convincing text decided to experiment with it to improve the Teaching Guides for performing the systematic Literature Reviews. Librarian was teaching this course to student entrepreneurs from past many semesters and already have good experience with it.

The experimentation with the ChatGPT further allowed the librarian to add more simple examples *(especially for new entrepreneurs)* to existing guide, as well improving existing text. For instance, the market research guide previously included complex terminologies and assumptions about the prior knowledge of entrepreneurs, making it harder for new entrepreneurs to understand. Some sections used terms like "demographic segmentation" and "qualitative data triangulation" without adequate explanation, which could be intimidating, especially for entrepreneurs from engineering backgrounds or those without marketing expertise. With the help of ChatGPT, the librarian rewrote this section in clearer, more accessible language, such as explaining "demographic segmentation" as "figuring out who your customers are based on their age, location, or interests". The updated guide also included step-by-step examples to make the process actionable, such as suggesting, "If you're opening a bakery, think about whether your primary customers might be families, students, or local businesses". Practical advice was added, like

running a quick poll on social media to test ideas or visiting competitor websites and social media profiles to identify gaps in the market. These changes transformed the guide into a more approachable and practical resource, enabling new entrepreneurs to tackle market research with confidence.

The reference librarian also explored integrating ChatGPT into research by creating a comprehensive guide on its use, specifically tailored to assist researchers in leveraging AI effectively. This guide included instructions on how to incorporate ChatGPT into various stages of the research process, such as conceptualisation, literature reviews, data analysis, drafting, and editting draft, while adhering to ethical and professional standards. Additionally, the guide provided clear steps for documenting and reporting AI contributions in research outputs, aligning with current policies of journal publishers. A customized version of the research guide was created for entrepreneurs interested in conducting research and finding solutions to their business problems using bibliographic databases, tailored to the stages conceptualized in Gupta and Gupta (2024). In the experimentation, no sensitive information was involved, and the revised guides were provided to patrons and made available for library members online.

Controlled experimentations

The consulting project does not involve accessing and sharing sensitive information with the technology. There are lot of librarian business support tasks that require sharing sensitive data with the technology. This aspect is one of the reasons why librarians hesitate to experiment with the technology as they don't want to share sensitive information with the technology. Additionally, lot of permissions will be required from the management to conduct these experimentations. This strategy involves carefully managed experimentation for high-frequency tasks that handle sensitive data. The focus is on ensuring that any experimentation is conducted with stringent data protection measures to maintain privacy and compliance.

In the consulting project, the reference librarian opted not to experiment with the new technology due to existing data regulations and lack of AI experimentation policies especially involving sensitive data. However, discussions were held about potential tasks that could benefit from AI integration with the librarian. The librarian noted that they frequently receive online reference queries, such as patrons requesting updated market research reports. One idea proposed was integrating ChatGPT with the library's online system to enhance service efficiency. In this scenario, ChatGPT could access patron information, such as the last report shared, and then retrieve the updated market research report from relevant databases, automatically delivering it to the patron. This would streamline the process and ensure patrons receive

Table 1. AI experimentation policy.

Purpose: This policy outlines the guidelines and principles for experimenting with AI technologies in the library, ensuring that such experiments are conducted responsibly, ethically, and in alignment with the organization's policies and existing regulations.
Scope: This policy applies to all AI-related experimentation within the library, including those that require sharing sensitive as well as non-sensitive AI technology. This policy does not apply for the implementation of the AI technology post successful experimentations. It covers all data types, with particular focus on sensitive data, and applies to all staff involved in AI-related projects.

Guiding Principles

Ethical AI Use: All AI experiments must adhere to ethical standards, ensuring fairness, transparency, and accountability.
Data Protection: Safeguarding patron and organizational data is paramount. Experiments involving sensitive data require heightened security measures.
Compliance: All AI activities must comply with relevant legal requirements, organizational policies, and data protection regulations.

AI Experimentation Strategies

This policy is guided by a 2x2 matrix based on two variables: Library Task Frequency and Data Sharing Necessity (sensitive data). The following strategies correspond to different combinations of these variables:

Proactive Optimization
Application: Frequent library tasks with no data-sharing necessity.
Strategy: Encourage frequent experimentation to library frequent tasks, for instance, improving the teaching guides (e.g., systematic literature review guides). Librarian is free to conduct any experimentation and must share the details of experimentations and its outcome on library knowledge sharing platform.

Controlled Experimentation
Application: Frequent library tasks with high data-sharing necessity.
Strategy: Implement AI cautiously, ensuring all experimental data is properly anonymized or synthetic data is used, in-house AI sandboxed are used (if available), and access to other data is restricted. Requires prior approval, close monitoring, and sharing details of conducted experimentations. Experimentation should be conducted as per approval conditions.

Opportunistic Experimentation
Application: Infrequent tasks with low data-sharing necessity.
Strategy: Allow flexible experimentation to explore new AI applications that could enhance less frequent tasks, like generating customized content for specific queries. Librarians have full flexibility to decide which experiments to conduct and when; but it is recommended only when there is a business case to undertake these, owing to limited resources library processes.

Conservative Approach
Application: Infrequent tasks with high data-sharing necessity.
Strategy: Limit or avoid experimentation unless there is a strong business case. If experimentation is necessary, apply the highest level of scrutiny and obtain explicit approvals as done for controlled experimentations.

Data Handling and Privacy

Data Classification: Librarians must classify data according to sensitivity levels before any AI experimentation. The existing library classifications can be used. In case particular data is not classified, use the library classification policy.

(*Continued*)

Table 1. (Continued).

Data Processing and Retention: AI tools must process data in line with the library's data retention policies. In no case the librarians will use the full dataset available with the libraries. The data handling procedures need to be mentioned for getting approvals for the experimentations involving sensitive data. The experimentation samples should be completely anonymized, or synthetic data could be used. The technology policies, for instance privacy policy and terms of use, should be reviewed to understand data handling practices.

Risk Management

Risk Assessment: All AI experiments *(those requiring sensitive data)* must undergo a risk assessment to identify potential privacy, security, ethical risks, data Retention Issues, third party sharing risks. The risk assessment will be done by the librarian willing to undertake AI experiments.

Experimentations Monitoring and Evaluation

All the successful and failed experiments must be documented, including objectives, key success indicators, details of experimentation *(prompts used, data shared with AI tool, outcomes, data handling practices)*, recommendations, and lessons learned. The details should be shared with the management and uploaded on library knowledge sharing platform. The monitoring and evaluation committee will continuously monitor the experimentations and may conduct evaluations *(formative and summative)* to see if the experimentations were able to meet library improvisation objectives. A post-experimentation review should be conducted to assess effectiveness and identify lessons learned.

Training, Awareness, and Institutional support

Staff Training: Librarians and staff involved in AI experimentation must be trained on the AI policy, data protection practices, ethical AI use, and design and conducting the experimentations.
Knowledge dissemination skills and training: Librarians will receive training on effectively disseminating experimentation details, outcomes, and lessons learned to their peers. This training will equip librarians with the skills needed to share insights and foster a culture of continuous experimentation. By promoting knowledge sharing, the training also supports both formative and summative evaluations, encouraging other librarians to engage in and build upon these experiments.**Continuous Learning**: Encourage ongoing education about advancements in AI technologies, evolving best practices in data protection and ethics, and learning from the peer's experimentations.
Institutional support: Librarians will receive support from both technical and legal teams. The technical team will assist with AI sandbox environments (if available), provide guidance on the AI technology under consideration, and manage the knowledge-sharing platform. The legal team will help librarians analyze technology contracts and navigate relevant data regulations.

Policy Review

This AI Experimentation Policy will be reviewed annually or as needed to accommodate new AI technologies, legal requirements, and organizational changes. Revisions will be made to ensure the policy remains relevant and effective.

Table 2. Controlled AI experimentation protocol (*as per AI experimentation policy).*

After identifying that sensitive data needs to be shared with the AI technology (based on the organization's data classification policy) for a highly frequent library task, the librarian should follow these steps to seek management approval and conduct experimentation in strict accordance with approval conditions.

(1) **Review Privacy and Contractual Documents**: Examine the technology's privacy policy and contractual documents to understand data processing, AI model training, data ownership, and retention practices. This will help the librarian to consider only those technologies for experimentation that has lowest risks associated with retaining shared data, for using it for training its AI models, and sharing with third parties.
(2) **Manage Experimentation Data**: If technology does not use sensitive data for training and does not retain information, decide on using synthetic or anonymized data, and assess the need for patron consent. The decision should only pertain to experimentation and not adoption of the technology. For instance, librarian would like to experiment with the AI technologies for automating the customer requests for updated market research reports, for which sensitive data will be required. In this case, librarian can use synthetic data that mirrors the characteristics of actual data or anonymized data (that does not represent the real patron). During real implementation, patron consent will be necessary. Although current experimentation may be preliminary, it provides valuable insights and experience that can support future experimentation and potential adoption of AI technologies.
(3) **Seek Management Approval**: Use the Controlled AI Experimentation approval form (Table 2) and submit it to management for approval, including details on data characterises, data protection measures, consent requirements, experimentation objectives, indicators, and risk assessment.
(4) **Conduct Experimentation**: Execute the experiment under the approved conditions, adhering to all data handling and privacy protocols. Use the controlled environment, for instance AI sandbox if provided by the IT team.
(5) **Report Results**: Document and report the results of the experimentation to management, highlighting how sensitive data was managed, outcome of the experimentations, and any implications for future adoption. Use the section 9 to 11 of Table 3 to report the findings.
(6) **Share the result**: Report on library knowledge platforms to provide insights and valuable information to other librarians for their reference and future experimentation.

timely and relevant information, with little efforts on the part of the reference librarians.

The proposed AI experimentation policy is tabulated in Table 1. Aligned with the policy, the recommended procedure to conduct controlled experimentations in the library and the necessary documentation is tabulated in Table 2 *(Controlled experimentation protocol)* and Table 3 *(Controlled experimentation request form)*. The idea is that the librarian must review the technology's privacy policy and other contracts with the support of legal teams, to understand data handling, retention, and AI model training processes. The analysis will then help librarians determine whether it is worthwhile to proceed to the next stage of seeking management approval for experimentation, considering the existing privacy regulations in place. The analysis can also help the librarian to come across alternative technologies or technology provider products that best align with library data regulations. For example, during the consulting meeting, the librarian mentioned that, based on a conversation with her legal expert friend, she learned about other ChatGPT variants that do not use user content for AI model training, such as ChatGPT for enterprise or alternative solutions like using OpenAI APIs.

If the decision is to move to the next stage, a detailed proposal is submitted for management approval (Table 2), ensuring anonymized data use where possible, and inhouse AI sandbox environments *(if available)* are used. For instance, Harvard University uses AI Sandbox environment to allow its

Table 3. Controlled AI experimentation approval and reporting form.

This form is to be filled and submitted to the library management through the manager for necessary approvals for conducting the controlled experimentation with sensitive data. Please fill sections 1 to 7 for the approval, and 9 to 11 for reporting the experimentation results.

(1) **Basic Information**
Librarian Name:
Department:
Date:

(2) **Technology Details**
AI Technology Name:
Provider:
Version:
Brief Description *(What does the AI tool do, and how will it be used?)*

(3) **Data Classification**
Type of Sensitive Data Involved: (e.g., personal information, proprietary data)
Data Classification Status: (as per organisation classification)
Details of the data *(what data will be used)*

(4) **Privacy and Contractual Review**
Privacy Policy Review: *(Yes/No)*
Contractual Documents Reviewed: *(Yes/No)*
Key Findings: *(e.g., data retention practices, data usage for AI model training, ownership of inputs and outputs, data shared with third parties)*

(5) **Experimentation Data Management**
Type of Data to be used for Experimentation: *(e.g., synthetic data, anonymized data)*
Is Patron Consent Required for experimentation? *(Yes/No)*
Details on Data Management: *(e.g., methods used for anonymization, data handling procedures)*

(6) **Experimentation Plan**
Objectives of Experimentation:
Key Indicators for Success:

(7) **Risk and Compliance Summary**
Key Risks Identified *(if any)* and probability of occurrence (1 to 5; 5 means highest):
Data Breach: Risk of unauthorized access to sensitive data.
Privacy Violations: Potential misuse of personal information if not properly anonymized.
Data Retention Issues: Data stored longer than necessary, increasing vulnerability.
Inaccurate AI Outputs: Risk of the AI generating misleading or incorrect information based on sensitive data.
Others *(if any)*
(The library will focus on technologies that does not retain the shared data, does not use it for training its AI models, and does not allow sharing with third parties. However, depending on the data handling procedures as reported by the librarians, exceptions can be made).

(8) **Management Approval**
Approval Status: (Approved/Denied)
Conditions for Approval:
Date of approval:

(9) **Implementation Details**
Controlled Environment Used: (e.g., AI sandbox)
Experiment Start Date:
Experiment End Date:
Details of experimentation *(prompts used, data shared with AI tool, outcomes, recommendations, and lessons learned, others)*

(10) **Reporting**
Report Submission Date:
Results Summary *(with interaction screenshots)*:
Implications for Future Adoption:

(11) **Other Relevant Information:**

faculties to experiment with Large Language Models (LLM) in their classrooms.[2] After experimentation, the librarians can share the outcomes with management to guide further adoption decisions and foster further experimentations. For experiments that do not involve sensitive data, the librarian has full discretion to proceed with the experiments, share the results with management, and make adoption decisions accordingly.

Opportunistic experimentation

This strategy emphasizes experimentation for low-frequency library tasks with low data sensitivity when a specific opportunity or need arises. The focus is on targeted experimentation when needs or opportunities for improvement become evident. Analyzing the library business support services, there are some tasks that are less frequent and do not involve sharing sensitive information. The librarian can experiment with the technology for the less frequent task, adapt the technology results as per information obtained from other sources, and improve the further interactions accordingly.

In the consulting project, reference librarian recalled how during the pandemic, one of the startups approached the library to seek instruction material for exporting to foreign countries in pandemic situations, especially understanding how to analyze multiple countries in fluctuating market conditions. The librarian used ChatGPT to create and improve the instruction guide they have since pandemic. This strategy implies that librarians can experiment with the technology for less frequent use cases as when there is a need or the opportunity to tap. There could be plenty of less frequent use cases *(known or unknown to the librarians)* that could accept delays in technology adoptions.

Conservative approach

This strategy involves avoiding or minimizing experimentation with low-frequency library tasks that handle high data sensitivity. Having experimented with the other tasks, delaying adoption technology for these tasks will help libraries avoiding investing in experimentations on less frequent tasks and avoid taking unnecessary risks associated with handling sensitive information. One example could be, Customized Reference Services for Unique Business Problems. This could involve providing highly tailored research and reference services for specific business problems, which involve detailed and sensitive information and should be approached conservatively. It is better to conduct this task using traditional methods (manually or using technologies that don't require data sharing) until and unless it is unavoidable.

Details of experimentations and their outcomes, regardless of the experimentation strategy employed, must be meticulously documented and shared with both library management and on the library's knowledge-sharing

platform. This documentation is crucial because experimentation reports will play a vital role in both formative and summative evaluations. This process can then be conducted by the librarian (with necessary evaluation skills), dedicated department for monitoring and evaluation (M&E), or by third-party specialists in M&E. This approach will ensure that the insights gained from experiments are systematically evaluated and used to inform future practices. These evaluations will help to ensure that experimentations are conducted effectively, with lessons learned being applied to future initiatives. The experimentations together help assess how well the AI policy is functioning and whether the experiments are contributing to the library's transformation and customer service improvement objectives (and others). This ensures that AI technologies are integrated in ways that not only align with the library's goals and regulatory requirements but also keep the library in step with ongoing innovations in the technological landscape.

AI experimentation policy

The consulting project resulted in the formulation of an AI Experimentation Policy that outlines the guidelines and principles for conducting AI technology-related experiments. This policy is designed to encourage ongoing experimentation while ensuring that all activities are carried out responsibly, ethically, and in compliance with existing regulations. Table 1 provides a detailed overview of the recommended AI experimentation strategies.

The Controlled Experimentation Protocol provides librarians with specific instructions on how to proceed with experiments involving sensitive data. It requires librarians to first consult the organization's data classification policy to identify sensitive data. Based on this classification, they choose an appropriate strategy from the provided framework. In case the data is classified as sensitive, the protocol involves reviewing the technology's privacy policy, and other contractual documents, to understand how sensitive data is processed, how AI model is trained, ownership of inputs and outputs, and how long data is retained by the technology. This allows librarians to determine if the technology can be used for experiments involving sensitive data, such as verifying whether the technology uses shared data for training its model. If the technology does not use sensitive data for training and does not retain information, librarians should identify how to manage experimentation data, such as using synthetic data that mirrors the characteristics of actual data or anonymized data and determine if obtaining consent from patrons is necessary. If decision is to go for the next step, the librarian needs to prepare a detailed proposal for management, conducting experiments under approval, and determine if obtaining consent from patrons is necessary. Results are then reported to management for informed adoption decisions. Table 2 shows the controlled AI experimentation protocol as suggested to the library.

AI Experimentation approval form is to request approval for experimenting with AI technologies that involves sharing sensitive data with these technologies, ensuring that sensitive data is protected according to existing data regulations and library policies in place. Table 3 gives the format of the form as recommended to the library at the end of the consulting project. The same form can also be used to report the experimentation outcomes.

AI experimentation policy implementation

The policy proposed in this article enables librarians to experiment with AI technologies while aligning with ethical standards and data regulations, sharing their outcomes to support monitoring and evaluation (M&E), and driving further innovations in subsequent experiments. An AI experimentation policy is essential because, through the discussions with library staff of many libraries, it became clear that while there is enthusiasm to experiment with AI technologies, the limitations – particularly around data sensitivity – often demotivate them from proceeding. This challenge fostered the motivation to design the framework that focuses on leveraging AI for tasks that are frequently conducted and involve little or no sensitive data. By prioritizing these activities, libraries can introduce AI in a controlled manner, ensuring a smoother digital transformation. The policy also includes provisions that allow librarians to experiment with sensitive data, once they are confident in their understanding and handling of the technology. Less frequently accessed tasks can be explored at a later stage, once librarians have gained more experience and identified clear use cases for these tasks.

To implement an AI experimentation framework in a library, it is recommended to follow a structured approach. For any experimentation, librarians should start by assessing the library's frequent tasks and data sensitivity needs. Utilize the AI experimentation strategy matrix to categorize these tasks and determine the appropriate strategy. For tasks that are frequent and involve no sensitive data, adopt the Proactive Optimization strategy, allowing for broader experimentation with AI technologies to explore potential benefits and efficiencies as well as to identify the possible use cases. The experimentation can also be conducted with the frequent library tasks with sensitive data sharing requirements. For this, apply the Controlled Experimentation strategy, ensuring compliance with the Controlled Experimentation protocol. Based on the circumstances, librarians can adopt the Opportunistic Experimentation strategy for areas where data sensitivity is low, but experimentation opportunities are sporadic, leveraging these chances to innovate when they arise. Conversely, use the Conservative Approach in rare cases.

Additionally, it is essential to establish robust institutional arrangements and support systems. Begin by setting up a collaborative framework involving the legal and IT teams to ensure compliance with data protection regulations

and to facilitate technical support for AI technologies. Create a knowledge-sharing platform, such as a dedicated space on the intranet or a shared drive, to document and disseminate experimentation results and insights.

Provide librarians with training on identifying data sensitivity, completing necessary permission forms, and documenting experimentation outcomes comprehensively. This training should equip them with the skills to ensure that reports not only detail the experimentation process but also allow management to evaluate both individual experiments and overall performance.

Develop a joint indicator framework to create coherence between experimentation success metrics and monitoring and evaluation (M&E) objectives. This framework will guide the assessment of AI experiments, promoting transparency and accountability. Foster a culture that values the sharing of both successful and unsuccessful experimentation outcomes, encouraging librarians to learn from each other's experiences and reflections. By promoting this culture of openness and continuous learning, libraries can drive innovation while maintaining rigorous standards for data privacy and ethical AI use. The proposed AI experimentation policy aims to create an environment of open innovation by encouraging collaborative knowledge exchanges and the ethical self-exploration of emerging technologies within existing regulations. It promotes flexibility and adaptability, driven by peer learning and collaborative experimentation, all grounded in real-world, practical experiences with technologies used in ongoing librarian activities. This approach fosters AI reskilling among librarians, as reskilling is reported to be driven by continuous learning, adaptability, collaborative exploration, and a hands-on, practical approach (Lo 2024a).

The proposed framework provides a structured approach to AI experimentation in libraries, but its successful implementation depends heavily on the knowledge and confidence of library directors and staff. Many library professionals may require further familiarity with critical concepts such as data sensitivity. This includes recognizing whether data is sensitive, converting real data into synthetic data (which requires understanding the sensitive elements of the data) and understanding the implications of sharing information with commercial large language model (LLM) service providers. Addressing these challenges is essential to ensure the framework's practical applicability across diverse library environments.

To bridge these knowledge gaps, it is crucial to provide foundational training on data handling and its implications. For example, synthetic data – artificially generated data that retains the statistical properties of real data – can be used as a substitute for sensitive information during experimentation. Unlike real data, synthetic data mitigates privacy risks, as it does not expose real user information to AI systems. Additionally, sharing data with commercial LLM service providers can introduce risks such as unauthorized data retention, model training on shared inputs, or noncompliance with privacy

regulations. Libraries must carefully evaluate these risks by thoroughly reviewing the AI tool's privacy policies and terms of use, focusing on data retention practices, data ownership, and third-party sharing. To assist libraries in this process, training programs are essential.

Most universities already have data classification policies in place, which provide necessary information about sensitive data and its usage protocols. These universities also have specialized departments that offer advice on legal and data-related issues. Since these resources are already available, imparting training on data privacy and security should not be a major challenge. For example, the legal department could create a checklist covering key aspects to review in technology usage policies, such as: "Does the AI tool explicitly state that it does not retain user data for model training?" Another checklist could be provided to help staff classify data as sensitive or insensitive under the university's data classification policy.

To empower library professionals further, it is important to integrate capacity-building initiatives into the implementation of AI experimentation strategies. Libraries can organize training sessions focused on data privacy, ethical AI practices, and risk assessment. Collaborating with academic institutions or technology providers can enhance these efforts, offering access to additional expertise and technical support. Furthermore, establishing knowledge-sharing platforms within libraries, such as intranet spaces or shared drives, can allow staff to exchange insights, experimentation outcomes, and best practices. These platforms could also be useful for identifying sensitive data and understanding technology data retention or training policies.

Finally, while the current paper introduces a robust framework, the importance of foundational data literacy deserves further exploration. A future study could focus on creating a comprehensive primer for library professionals, detailing the types of data libraries collect, the implications of data sharing, and the ethical considerations of using AI technologies. This primer could complement the current framework by equipping librarians with the essential knowledge required to navigate the complexities of AI experimentation confidently. By addressing these knowledge gaps and proposing practical solutions, this paper aims to ensure that the framework is accessible and actionable for all library professionals, enabling responsible and effective AI experimentation in diverse library settings.

Concluding remarks and recommendation

In conclusion, the framework outlined in this paper provides librarians with a practical approach to experimenting with AI technologies while maintaining a strong focus on data privacy and compliance. By categorizing library tasks based on their frequency and the necessity for data sharing, librarians can choose the most appropriate experimentation strategy, whether it involves

frequent experimentations or more controlled, data-sensitive experiments. The library's data classification system will aid in assessing the sensitivity of data used in AI experiments, while the librarian's experience in supporting businesses can help identify frequent library tasks that could benefit most from AI experimentation. Integrating AI technologies into these frequent tasks, where no sensitive data sharing is required, is likely to deliver significant business value. Experimentation can also be conducted on library tasks that require sensitive data sharing with the technology, albeit under strict data regulations. As an outcome of the consulting project, a proposed AI experimentation policy outlines strategies for handling sensitive data during these experiments. Librarians have full flexibility to experiment when no sensitive data is involved, but for tasks involving sensitive data, they must adhere to the library's protocols for controlled experimentation. For experiments involving sensitive data, libraries need to collaborate with legal experts to help librarians understand legal contracts, such as technology privacy policies, and with technical experts to get an access to the necessary technical environment, such as AI sandboxes, for conducting these experiments. Finally, since experimentation reports are essential for both formative and summative evaluations, libraries must either train librarians in these skills, establish a dedicated department for monitoring and evaluation (M&E), or engage third-party specialists in M&E to handle this aspect. The successful implementation of AI experimentation in libraries requires that librarians understand how to handle sensitive data, use synthetic data, and assess the risks of sharing information with commercial AI providers. By providing targeted training, practical tools, and promoting collaboration, libraries can ensure responsible and effective AI usage.

Notes

1. https://infosec.ed.ac.uk/how-to-protect/encrypting/use-cases/short-definition-of-sensitive-data.
2. https://harvard.service-now.com/ithelp?id=kb_article&sys_id=ca9dd14447f07950566cf147536d433b.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research is funded by the European Union's Horizon research and innovation program (Project ID: [101061516], Project Acronym: LibrarIN). The paper was also co-funded by the Faculty Research and Innovation Grant of Gisma University of Applied Sciences, Potsdam,

Germany) Project ID: [RGVG_02], Project Acronym: DIGEnt). This publication solely reflects the views of the authors, and the funding agencies cannot be held responsible for any use that may be made of the information contained therein. The funders had no involvement in the execution of the study protocol and reporting, including data collection, analysis, decision to publish, or preparation of the manuscript communicating research findings.

Notes on contributor

Varun Gupta received his Doctorate (cum laude) in Organizational Engineering, Doctorate (International/European Doctorate, Cum Lade) in Economics and Business Management, as well as in Computer Science and Engineering. He also earned his MBA (General), Máster en Dirección Internacional de Empresas, Master of Technology (By Research) in Computer Science & Engineering, and Bachelor of Technology (Hons.) in Computer Science & Engineering. He is a Professor of Digital Innovation and Director of the Multidisciplinary Research Centre for Innovations in SMEs (MrciS) at Gisma University of Applied Sciences, Potsdam, Germany. He is also a researcher at Universidad de Alcalá (Spain). Previously, he was associated with University College London (UCL), London (UK), University of Toronto (Canada), Leicester University (United Kingdom), Software Engineering Research Group (SERG), Lund University (Sweden), Sapienza Università di Roma (Italy), Free University of Bozen-Bolzano (Italy), University of South-Eastern Norway (Norway), Poznań University of Technology (Poland), Uniwersytet Szczeciński (Poland). Prof. Gupta is an Associate Editor of IEEE Access (an SCIE-indexed publication of IEEE), PeerJ Computer Science (an SCIE-indexed publication of PeerJ), and the International Journal of Computer Aided Engineering & Technology (a Scopus-indexed publication of Inderscience Publishers). He is a former editorial team member of the British Journal of Educational Technology (BJET) (an SCIE-indexed publication of Wiley), PLOS One (an SCIE-indexed publication of PLOS), and the Journal of Cases on Information Technology (ESCI and Scopus-indexed publication of IGI Global). Prof. Gupta has worked on multiple projects supported by various agencies such as the European Union and the Spanish National Programme. His areas of interest include evidence-based software engineering, innovation management, digital transformations and innovation, technology adoption in SMEs, entrepreneurship, and international business management.

ORCID

Varun Gupta http://orcid.org/0000-0003-2824-3402

Institutional review board statement

The conducted study was approved by the Institutional Review Board of Gisma University of Applied Sciences, Potsdam, Germany under protocol number 010424.

References

Ajani, Y. A., A. Tella, K. Y. Yetunde Salawu, and F. Abdullahi. 2022. Perspectives of librarians on awareness and readiness of academic libraries to integrate artificial intelligence for library operations and services in Nigeria. *Internet Reference Services Quarterly* 26 (4):213–30. doi: 10.1080/10875301.2022.2086196.

American Library Association. 2023. Libraries build business. Accessed August 1, 2024. https://alair.ala.org/server/api/core/bitstreams/2e276162-edb2-4fbc-9d2b-26ba8eb43691/content.

Aregbesola, A., S. Emmanuel Owolabi, and T. Adebisi. 2024. Going to the cities: The strategic roles of public libraries in promoting sustainable development goals. *Public Library Quarterly* 43 (3):367–84. doi: 10.1080/01616846.2023.2253692.

Echedom, A. U., and O. Okuonghae. 2021. Transforming academic library operations in Africa with artificial intelligence: Opportunities and challenges: A review paper. *New Review of Academic Librarianship* 27 (2):243–55. doi: 10.1080/13614533.2021.1906715.

Fui-Hoon Nah, F., R. Zheng, J. Cai, K. Siau, and L. Chen. 2023. Generative AI and ChatGPT: Applications, challenges, and ai-human collaboration. *Journal of Information Technology Case & Application Research* 25 (3):277–304. doi: 10.1080/15228053.2023.2233814.

Gupta, V. 2024a. *Libraries as hubs for entrepreneurship*. Germany: Springer. (In Press).

Gupta, V. 2024b. Innovating library services: Co-creation, experimentation, and enhanced business value tool for technological advancements. *Public Library Quarterly* 1–17. doi: 10.1080/01616846.2024.2364522.

Gupta, V. 2024c. From hype to strategy: Navigating the reality of experimental strategic adoption of AI technologies in libraries. *Reference Services Review*. doi: 10.1108/RSR-08-2024-0042.

Gupta, V., and C. Gupta. 2023a. Experimentation-driven frameworks for AI technology adoption in libraries: Practical implementation in the library. *College & Undergraduate Libraries* 30 (3):95–103. doi: 10.1080/10691316.2023.2266819.

Gupta, V., and C. Gupta. 2023b. Synchronizing innovation: Unveiling the synergy of need-based and curiosity-based experimentation in AI technology adoption for libraries. *Library Hi Tech News* 40 (9):15–17. doi: 10.1108/LHTN-07-2023-0127.

Gupta, V., and C. Gupta. 2024. Transforming entrepreneurial research: Leveraging library research services and technology innovations for rapid information discovery. *Online Information Review* 48 (3):491–99. doi: 10.1108/OIR-04-2023-0156.

Gupta, V., and L. Rubalcaba. 2022. University libraries as open innovation partners: Harnessing hidden potential to foster global entrepreneurship. *The Journal of Academic Librarianship* 48 (2):102432. doi: 10.1016/j.acalib.2021.102432.

Harvard University. Data security levels and research data examples. Harvard University Privacy and Security. Accessed August 2, 2024. https://privsec.harvard.edu/data-security-levels-research-data-examples.

Kaushal, V., and R. Yadav. 2022. The role of chatbots in academic libraries: An experience-based perspective. *Journal of the Australian Library and Information Association* 71 (3):215–32. doi: 10.1080/24750158.2022.2106403.

Lo, L. S. 2024a. Transforming academic librarianship through AI reskilling: Insights from the GPT-4 exploration program. *The Journal of Academic Librarianship* 50 (3):102883. doi: 10.1016/j.acalib.2024.102883.

Lo, L. S. 2024b. Evaluating AI literacy in academic libraries: A survey study with a focus on US employees. *College & Research Libraries* 85 (5):635–S668. doi: 10.5860/crl.85.5.635.

Nehra, S. S., and S. Y. Bansode. 2024. Exploring the prospects and perils of integrating artificial intelligence and ChatGPT in Academic and Research Libraries (ARL): Challenges and opportunity. *Journal of Web Librarianship* 18 (3):111–32. doi: 10.1080/19322909.2024.2390413.

Panda, S. K., A. Bhatt, and A. Satapathy. 2024. ChatGPT and its role in academic libraries: A discussion. *New Review of Academic Librarianship* 30 (4):422–36. doi: 10.1080/13614533.2024.2381510.

Poll, R., and P. Payne. 2006. Impact measures for libraries and information services. *Library Hi Tech* 24 (4):547–62. doi: 10.1108/07378830610715419.

Urquhart, C. 2018. Principles and practice in impact assessment for academic libraries. *Information and Learning Science* 119 (1/2):121–34. doi: 10.1108/ILS-06-2017-0053.

Winkler, B., and P. Kiszl. 2022. Views of academic library directors on artificial intelligence: A Representative survey in Hungary. *New Review of Academic Librarianship* 28 (3):256–78. doi: 10.1080/13614533.2021.1930076.

Yim, M., M. Fellows, and C. Coward. 2020. Mixed-methods library evaluation integrating the patron, library, and external perspectives: The case of Namibia regional libraries. *Evaluation and Program Planning* 79:101782. doi: 10.1016/j.evalprogplan.2020.101782.