



Beyond technical performance: Preliminary findings on algorithm aversion in digital library environments

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Abstract

Introduction. This study examines algorithm aversion in digital library contexts, where users increasingly encounter algorithm-enabled services. Prior research in healthcare and finance shows that users often resist algorithmic systems even when they outperform human alternatives, yet little is known about how this phenomenon manifests in the digital libraries context.

Method. As part of an ongoing project, we conducted semi-structured interviews with 18 users from two Chinese universities. Participants were selected through theoretical sampling. Interviews were analysed using constructivist grounded theory.

Analysis. Open and axial coding of the first 18 interviews produced 42 initial concepts organised into 16 categories under five dimensions: algorithmic, platform, individual, task, and cognitive factors.

Results. Preliminary findings suggest that algorithm aversion in digital libraries is multidimensional. Users reported concerns about inaccurate or irrelevant results, cumbersome interfaces, lack of familiarity, and limited trust in recommendations. These patterns suggest that aversion is shaped by both technical shortcomings and user-level factors, leading to frustration, avoidance, and reliance on manual methods.

Conclusion(s). These early insights extend algorithm aversion research into a complex service environment, offering evidence that resistance arises from the interplay of technical, individual, and contextual conditions. The ongoing study will expand the dataset and employ DEMATEL to identify causal relationships among factors.

Introduction

Digital library services have increasingly integrated algorithmic technologies to enhance the user experience and improve the efficiency of information access. These algorithm-enabled services encompass intelligent consultation robots, personalised recommendation systems, smart search platforms with automated ranking, and adaptive interface features designed to facilitate the discovery of information. However, research from other domains that adopted algorithmic technologies earlier, such as healthcare (Bankuoru Egala & Liang, 2024; Shaffer et al., 2013) and finance (Filiz et al., 2021, 2022), reveals a persistent challenge: users often exhibit resistance to algorithmic systems, even when they demonstrate better performance. This phenomenon, called algorithm aversion, was originally defined by Dietvorst et al. (2015) as the tendency to avoid algorithms after observing them make errors, even when they outperform human alternatives. Since its initial formulation, the concept of algorithm aversion has evolved considerably. While early studies focused on controlled laboratory settings where algorithmic superiority was experimentally demonstrated, contemporary research has expanded to examine algorithm aversion as a broader resistance pattern in real-world implementations (Mahmud et al., 2022). This expanded understanding recognises that algorithm aversion may manifest differently in complex service environments where multiple algorithmic features operate simultaneously and where establishing clear performance benchmarks proves methodologically challenging.

In digital library contexts, algorithm aversion exhibits unique characteristics that distinguish it from algorithm resistance observed in other domains. Unlike simple decision-making situations examined in laboratory studies, digital library users interact with multiple connected algorithmic services that serve different purposes within complex information-seeking processes. Users may, at the same time, encounter intelligent search algorithms, personalised recommendation systems, automated classification tools, and smart interface features, each with different levels of complexity and user transparency. This multi-layered algorithmic environment creates opportunities for resistance patterns that may not appear in studies focusing on single algorithmic decisions.

Despite the growing use of algorithmic features in digital libraries and the investment in developing these technologies, limited research has examined how algorithm aversion appears specifically within library and information science contexts. To address this gap, our ongoing project aims to investigate algorithm aversion among digital library users in Chinese university settings using a grounded theory methodology. The preliminary findings reported in the short paper represent initial coding results from the first 18 interviews, demonstrating the emergence of five primary factor categories with 16 subcategories that contribute to algorithm aversion in digital library environments. This study is expected to contribute to the algorithm aversion literature by extending theoretical understanding to complex service environments and providing insights relevant to both academic research and the development of practical algorithmic technologies in library settings. For researchers, the study offers domain-specific factors and patterns that may inform future experimental studies of algorithm aversion in library contexts. For practitioners, the findings guide the design of algorithmic features that address user concerns and resistance factors identified through systematic qualitative analysis.

Although the analysis is still in progress, the findings reported here demonstrate how user resistance unfolds in digital libraries and point to strategies that can inform both theoretical development and the design of user-centred algorithmic services.

Literature review

Origins of algorithm aversion

Algorithm aversion research originated from studies comparing human judgment with statistical models in clinical settings. Early work showed that even when statistical models predicted

outcomes more accurately, people preferred human judgment (Meehl, 1954). This pattern extended to business (Jussupow et al., 2024) and communication research (Huprich & Nelson, 2015), where people distrusted automated systems due to perceived impersonality and complexity. Dietvorst et al. (2015) provided direct experimental evidence that participants abandoned algorithms after observing errors, even when algorithms remained more accurate overall. Subsequent studies revealed that resistance can occur before seeing failures, suggesting deeper concerns beyond error reactions (Dietvorst et al., 2018). However, research also identified contexts where algorithmic trust is higher, such as estimation tasks or popularity predictions (Logg et al., 2019), indicating that algorithm aversion varies by context and task type.

Conceptual definitions of algorithm aversion

Algorithm aversion research has developed along two distinct definitional approaches that reflect fundamental differences in methodological assumptions and research contexts.

The narrow definition, established by Dietvorst et al. (2015, 2018), requires demonstrated explicit algorithmic superiority as a prerequisite. Under this approach, algorithm aversion occurs when individuals avoid algorithms despite knowing they perform better than human alternatives. This conceptualisation emphasises irrational rejection in controlled experimental settings, which is more common in clinical or financial services settings.

A broader conceptualisation treats algorithm aversion as general resistance to algorithmic systems, regardless of demonstrated performance superiority. Scholars recognise that establishing algorithmic superiority is often methodologically challenging in real-world contexts (Burton et al., 2020). Prah and Van Swol (2017) described it as irrational discounting of automated advice, while Jussupow et al. (2020) characterised it as biased evaluation leading to negative judgments. Contemporary research increasingly adopts this broader view to examine resistance in complex service environments, including both behavioral rejection and negative emotional responses (Mahmud et al., 2022).

This study adopts the broader conceptualisation for digital library contexts, where users interact with multiple algorithmic services within complex information-seeking workflows. Algorithm aversion manifests as consistent resistance patterns toward algorithmic features, including avoidance behaviors and negative attitudes such as doubt, frustration, and dissatisfaction with algorithmic services.

Factors influencing algorithm aversion

Research identifies three main categories of factors influencing algorithm aversion: algorithm characteristics, individual characteristics, and task characteristics.

Algorithm characteristics include transparency, complexity, response speed, accuracy, learning ability, intervention level, modifiability, and anthropomorphism. Dzindolet et al. (2002) demonstrated that unclear algorithm operation mechanisms foster aversion emotions. Burton et al. (2020) found that people dislike complex algorithms, judging them as unnatural threats to human uniqueness. Efendić et al. (2020) reported that slow response times lower confidence in algorithmic outputs, while Schneider and Leyer (2019) noted that algorithmic errors receive harsher punishment than human errors. Studies show resistance can be reduced when algorithms demonstrate learning ability (Berger et al., 2020) or allow user modification (Dietvorst et al., 2018). Bigman and Gray (2018) found less aversion when algorithms act as assistants while humans retain final control. Anthropomorphic features present mixed effects. For example, Srinivasan found they increase harm responsibility perceptions (Srinivasan & Sarial-Abi, 2021).

Individual characteristics affecting algorithm aversion include gender, experience, knowledge, expertise, identity, control orientation, and performance expectations. Dietvorst et al. (2015) found that women often show greater willingness to accept algorithmic suggestions due to lower

confidence in professional skills. Lourenço et al. (2020) demonstrated that prior interactions affect subsequent algorithmic advice usage. Algorithm knowledge generally increases acceptance, but professional individuals often show higher aversion due to domain expertise (Bigman & Gray, 2018; Gaube et al., 2021). Leung et al. (2018) found that stronger identity leads to rejection of automated products that threaten professional skills. Shaffer et al. (2013) showed that people with stronger personal control beliefs exhibit greater algorithm resistance. Dzindolet et al. (2002) noted that unrealistic expectations of algorithmic perfection intensify aversion when errors occur.

Task characteristics moderate algorithm aversion across contexts, including objectivity, importance, uncertainty, creativity, and investment costs. Castelo et al. (2019) and Logg et al. (2019) observed greater trust for objective versus subjective tasks, with Castelo's review revealing a positive correlation between perceived objectivity and algorithm application frequency. Castelo et al. (2019) also demonstrated that task importance increases aversion, while Dietvorst et al. (2015) found that uncertainty reduces algorithm willingness. Gino (2008) showed that people prefer paid over free algorithmic advice, and Sutherland et al. (2016) found that investment creates commitment through sunk cost effects. Bigman and Gray (2018) highlighted that moral sensitivity strengthens algorithm aversion when tasks involve ethical choices.

Research methodology

Research design

This study uses a grounded theory approach to explore the formation and expression of algorithm aversion in digital library contexts. Grounded theory is well-suited for this purpose because algorithm aversion in libraries remains underexplored, and the method allows for theory-building directly from empirical data. Semi-structured interviews were chosen as the main data collection method to capture detailed user perceptions, experiences, and attitudes.

As emphasised above, this study adopts the broader conceptualisation of algorithm aversion that includes general resistance to algorithmic systems rather than requiring demonstrated algorithmic superiority first. We define **algorithm aversion** in this study as **the attitude or behavior of neglecting algorithmic decisions in favor of one's own decisions or alternative approaches to obtain required resources**. This definition includes both behavioral dimensions (including doubt and rejection of algorithmic results, resistance and refusal to use algorithmic features) and attitudinal dimensions (including negative emotions toward algorithmic systems and dissatisfaction with algorithmic services).

Digital library services integrating algorithmic technologies in this study include intelligent consultation robots, intelligent book recommendation systems, personalised subject resource recommendations, and one-stop search platforms with intelligent retrieval and resource ranking algorithms.

Data collection

The interview protocol development followed three stages. The first stage involved designing an initial protocol based on algorithm aversion factors identified in existing literature. The second stage included expert consultation with three library science faculty to ensure question relevance, clarity, and comprehensive coverage of digital library service areas. The third stage was pilot testing with three users to refine question wording, identify potential ambiguities, and optimise interview flow. The final interview protocol includes questions on users' familiarity with algorithm-enabled digital library services, their perceived advantages and shortcomings, and specific experiences of resistance or abandonment. Sample questions included: 'Describe a recent experience using [specific algorithmic service such as intelligent search or personalised recommendations]—what happened and how did you feel about it?'; 'Have you ever avoided or stopped using algorithmic features in the digital library? Walk me through that specific decision and what led

to it'; 'When seeking information for your research, how do you decide between using algorithmic tools versus other methods?' Follow-up probes encouraged participants to provide specific examples, elaborate on their emotional responses, and explain their reasoning in detail. Basic demographic information and usage frequency were collected to provide context.

Participants were recruited from two Chinese universities using theoretical sampling principles to capture diversity in academic background and digital library usage. Eligibility required at least six months of experience with digital library services and prior interaction with algorithmic features. This is an ongoing project, and data collection uses both online and face-to-face formats to accommodate participant preferences and scheduling constraints. This paper reports findings from the first 18 interviews. Those interviews lasted between 45 and 75 minutes, with an average duration of 58 minutes. All interviews were audio-recorded with explicit participant consent following institutional IRB approval. Sampling will continue until theoretical saturation is reached, which means the interview will be stopped when the interviewee can no longer propose new categories and relationships, with follow-up verification by at least three participants.

Data analysis

Participants were assigned anonymous codes P1 through P18 to protect confidentiality. Interview transcripts were analysed using Charmaz's (2014) constructivist grounded theory approach through open coding, axial coding, and constant comparison.

Open Coding

Initial line-by-line coding examined interview transcripts systematically, with each sentence or meaningful phrase analysed for conceptual content related to algorithm resistance experiences. This process generated **initial concepts** representing specific manifestations of algorithm aversion behaviors and attitudes. When participant P7 described intelligent search problems, stating 'When I use the smart search for machine learning papers in medical diagnosis, the system returns general AI articles that don't match my specific research focus,' this was coded as initial concepts 'inaccurate search results', and 'limited natural language understanding.' When participant P3 discussed recommendation inadequacies, explaining 'The personalised book recommendations keep suggesting undergraduate textbooks when I need advanced research materials,' this was coded as initial concepts 'irrelevant algorithmic recommendations' and 'incomplete recommendation coverage.' Initial concepts supported by fewer than six participants or appearing only in limited-service contexts were noted as provisional themes requiring additional validation through subsequent data collection.

Related initial concepts were systematically grouped into **categorisations** through multiple rounds of comparison. The categorisation process examined initial concepts for conceptual similarities and shared properties related to digital library service experiences. Initial concepts such as 'inaccurate search results,' 'incorrect keyword extraction and processing,' and 'inadequate algorithmic reasoning capabilities' were grouped under categorisations Search Result Accuracy (A1) and Search Result Intelligence (A4) based on their focus on algorithmic performance problems. Initial concepts related to 'convoluted authentication procedures,' 'complex search query configuration,' and 'cumbersome page navigation process' were grouped under categorisation Operation Process (A7), reflecting platform usability concerns.

Axial coding

Following open coding, axial coding grouped the individual categorisations into higher-order themes through constant comparison and theoretical analysis. The 16 categorisations (A1-A16) were systematically examined for conceptual relationships and shared theoretical properties to identify broader dimensional constructs.

Categorisations A1 (Search Result Accuracy), A2 (Search Result Relevance), A3 (Search Result Complexity), and A4 (Search Result Intelligence) were grouped under Algorithmic Factors based on their common focus on core algorithmic performance and output quality issues. Categorisations A5 (Response Speed), A6 (System Functionality), A7 (Operation Process), A8 (Interface Design), and A9 (Business Promotion) were consolidated under Platform Factors, reflecting system design and operational characteristics that mediate user-algorithm interactions.

Individual Factors emerged from grouping A10 (User Familiarity), A11 (Information Literacy), and A12 (Personal Preferences and Habits), representing user characteristics that influence algorithmic acceptance. Task Factors combined A13 (Task Complexity) and A14 (Task Urgency) based on their shared focus on contextual information-seeking requirements. Finally, Cognitive Factors integrated A15 (Perceived Risk) and A16 (Perceived Usefulness), capturing users' evaluative assessments of algorithmic systems.

This axial coding process revealed five main theoretical dimensions that collectively explain algorithm aversion formation in digital library contexts, with each dimension representing distinct but interrelated aspects of user-algorithm interactions.

Preliminary findings and future research

Based on the analysis of the first 18 interviews, we identified 16 categories, including 42 initial concepts that contribute to algorithm aversion in digital library environments (Table 1). These categories cover algorithmic, platform, individual, task, and cognitive dimensions, and they highlight how technical features, personal characteristics, and situational demands interact to shape user resistance.

Axial Coding		Open Coding
Algorithmic Factors	Categorisation	Initial Concept
	A1 Search Result Accuracy	Inaccurate search results Incorrect keyword extraction and processing
	A2 Search Result Relevance	Low relevance of search results Overly broad and generic results Outdated search outputs
	A3 Search Result Complexity	Disorganised intelligent search outputs Overly complex result classification schemes
	A4 Search Result Intelligence	Inadequate algorithmic reasoning capabilities Limited natural language understanding Poor ranking logic
Platform Factors	A5 Response Speed	Slow system responsiveness Delayed algorithmic updates
	A6 System Functionality	Incomplete analytical capabilities Limited interactive capabilities
	A7 Operation Process	Authentication synchronisation delays Convolutd authentication procedures Complex search query configuration Cumbersome page navigation process Restrictive access control mechanisms
	Categorisation	Initial Concept
	A8 Interface Design	Limited display functionality Poor interface usability Lack of personalisation options Overly complex search interfaces
Individual Factors	A9 Business Promotion	Insufficient system orientation Inadequate service promotion Lack of user feedback mechanisms
	A10 User Familiarity	System unfamiliarity Reliance on subjective experience
	A11 Information Literacy	Limited domain expertise Insufficient search skills
	A12 Personal Preferences and Habits	Entrenched usage patterns Not interested in digital library services
Task Factors	A13 Task Complexity	Simple information needs Routine daily inquiries Ambiguous search objectives
	A14 Task Urgency	Urgent information requirements
Cognitive Factors	A15 Perceived Risk	Privacy concerns Intellectual property
	A16 Perceived Usefulness	Incomplete recommendation coverage Repetitive content suggestions Homogeneous recommendation

Axial Coding	Open Coding
	Irrelevant algorithmic recommendations

Table 1. Algorithm aversion factors in digital library environments

Participants often attributed resistance to the shortcomings of the algorithms themselves (A1-A4). Complaints included inaccurate outputs, errors in keyword processing, irrelevant or outdated results, cluttered displays, and weak ranking logic. Users felt that systems could not fully understand nuanced queries or distinguish what was truly important. These issues quickly eroded trust, suggesting that perceived failures in accuracy and relevance are central triggers of aversion.

Barriers also arose from how platforms operated and presented information (A5-A9). Users described slow response speeds, limited interactive functions, and cumbersome processes such as complex logins, query configurations, and navigation. Poor interface clarity, lack of personalisation, and overwhelming layouts further discouraged engagement. Some participants also noted insufficient promotion and orientation, which left them unaware of available features. Collectively, these issues show that system design and communication problems amplify aversion even when algorithmic capacity is adequate.

User characteristics (A10-A12) also shaped reliance on algorithmic services. Some participants admitted they were unfamiliar with the systems or relied on personal habits rather than new tools. Limited subject knowledge and insufficient search skills also reduced confidence in using intelligent features. Others expressed low motivation or disinterest in digital library services overall. These findings highlight that algorithm aversion is not only a matter of system performance but also of user readiness and skill.

The type and urgency of information needs (A13-A14) also influenced whether users relied on algorithmic support. For simple or routine tasks, participants felt algorithms added little value. When objectives were vague, they doubted whether the system could interpret their intent. Under time pressure, users often abandoned algorithmic tools, preferring manual methods they perceived as more efficient and reliable. This suggests that aversion is situational, varying with the complexity and stakes of the task.

Some resistance reflected broader judgments about system trustworthiness and value (A15-A16). Concerns about privacy and intellectual property made participants cautious about relying on intelligent features. Others questioned the usefulness of recommendation systems, noting incomplete coverage, repetitive content, and irrelevant suggestions. These perceptions show that algorithm aversion is shaped not only by immediate performance but also by how users weigh risks and benefits in the broader context of academic work.

These preliminary findings demonstrate that algorithm aversion in digital libraries is multidimensional, combining technical, personal, and contextual influences. Future research will expand interviews until theoretical saturation is reached and refine relationships among categories through further coding. A key next step is applying the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. DEMATEL will allow us to map causal relationships among the identified factors, distinguishing between root causes and resulting effects. This approach can identify the most influential drivers of algorithm aversion, providing clearer guidance for theory building and practical design strategies.

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