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Information Filtering, Evaluative Information Overload, and User Satisfaction in Digital Libraries: Evidence from a PLS-SEM Study

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This research examines structural relationship between information filtering, information overload and user satisfaction in the context of digital library environments. Even though information filtering typically assumed to decrease cognitive burden, very little empirical evidence explained how information filtering mechanisms affects evaluative cognition and satisfaction in information intensive academic systems. The survey data was analysed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach, with 390 active digital library users' respondents.

The results show that information filtering has a positive and significant effect on perceived information overload ($\beta = 0.236$, $p < 0.001$), suggesting that access to information resources that are rich with information relevance can increase evaluative cognitive demands in digital information interaction. Significantly also, Perceived information overload was related to user satisfaction ($\beta = 0.158$, $p = 0.003$), indicating that as perceived information overload increases, user satisfaction with digital library use might also increase.

It is a constructive evaluative state resulting from environments in which people retrieve information that are relevance-intensive and not just a negative cognitive state, which is what people have been thinking of perceived information overload up until now. Besides, mediation analysis which shows that perceived information overload completely mediated the relationship between information filtering and user satisfaction, and the direct relationship between information filtering and user satisfaction was not statistically valid ($\beta=0.091$, $p>0.05$).

The findings have implications for digital library scholarship, showing how evaluative cognitive engagement can be an important explanatory mechanism of the linkage between information filtering processes and user satisfaction in today's digital knowledge environments.

Keywords: Digital Libraries; Information Filtering; Evaluative Information Overload; User Satisfaction; Cognitive Engagement; PLS-SEM.

1 Introduction

Digital libraries are no longer just a repository of digitised content but are now dynamic systems of information, enabling the discovery, access and user-centered knowledge services. As significant infrastructures used in the modern academic world, they combine collections, databases and platforms to improve the search and research information communication. According to recent research, service quality, technological complexity, and prompt response to user expectation are the most important factors in determining whether digital library systems are effective or not instead of the size of collections (Khoeini et al., 2024; Khaydarova et al., 2026). Their use today is in the academic sphere as a pivot infrastructure for the integration of collections, databases and digital environments for information retrieval and academic communication (Rahman *et al*., 2026).

Yet, with the advent of digital information resources, the problem of information overload has worsened. The information overload is defined as when the quantity and complexity of information sources surpass the cognitive information handling capacity of users which affects their judgement, decision making and system experience (Arnold et al., 2023; Shahrzadi et al., 2024). Overload in digital library contexts can be caused not just by abundance of information, but also through the necessity to navigate systems featuring metadata overload, multiple results of search engines and competing sources that are relevant. It is a big theoretical issue in the broader context of Library and Information Science whether algorithmic support systems can

reduce the users' cognitive load, or they shift it to the higher order assistive work of scholarly search. A focus like this is in line with the already established work of ALIS in relation to scholarly communication, bibliometric visibility and the new structure of LIS research publication (Prieto-Gutiérrez and Segado-Boj, 2019).

Digital libraries have been adopting information filtering mechanisms such as ranking algorithms, relevance-based retrieval systems, recommender systems and personalised search functionality to deal with this problem. These should be aids to help people navigate effectively by prioritising content that may be of value and align the results of retrieval with the needs of users. Through experiments, it has been demonstrated that one of the fundamental properties of user-centered digital libraries design that contributes to the increased effectiveness of retrieval and personalisation is filtering (Khavidaki et al., 2023; Mitreva et al., 2026).

However, few empirical evidence in a Digital Library context helps explain what it means that the phenomenon of filtering reduces cognitive load or transforms it into the burden of evaluating. In practice, filtering may lead to increased exposure to a range of very relevant materials and users must compare, evaluate and synthesise competing materials. This suggests that overload can not only be informational overload, but evaluative overload that can be produced in relevance rich retrieval environments.

User satisfaction is highly related to perceived usefulness, system performance and general information experience and is considered as one of the key metrics of usefulness of digital libraries. In previous studies, the importance of satisfaction in sustaining the use of digital library systems, trust, and engagement with digital library systems has always been obvious (Zhang, 2022; Misra *et al*., 2023; Lei *et al*., 2026). How users rate such experiences, in the high information demand conditions, will therefore be key to optimising a service and designing an interface.

Although numerous research studies on digital libraries, personalisation and overload have been published, there are only a few studies that empirically examined these structural interrelationships in an explanatory context. The current research tends to presuppose that filtering will decrease overload, but the given assumption has not been thoroughly tested in actual conditions in digital libraries.

In this context, the paper attempts to study structural association of information filtering, information overload and user satisfaction in a digital library context. The research is drawn from the cognitive load theory and information behaviour perspectives and reveals the user's processing of retrieval complexity in the academic context where information is the focus of activity, and evaluation of the system's outcome.

Specifically, the article re-conceptualizes information overload as an evaluative state that occurs because of relevance endowed information retrieval environments and in this way demonstrates that filtering and satisfaction are completely mediated by it.

1.1 Research Objectives

1. To assess the effect of information Filtering on Perceived information overload in digital library settings.
2. To examine the effect of perceived information overload on user satisfaction with digital library systems.
3. To test whether information overload mediates the relationship between information filtering and user satisfaction.

2. Literature Review

2.1 Digital Libraries and Information-Rich Search Environments

The digital libraries have been transformed into repository-based systems to become active knowledge discovery and fora of scholarly communication. they are treated as active networks that are used to retrieve information from collection of scales, metadata system, algorithmic retrieval and user interface rather than passive information storage systems (Khalid *et al*., 2025; Islam et al., 2025).

As they become more sophisticated one would require a complex output of a search and several sources that are relevant and have a lot of metadata to gain access to it successfully. However, with the digital libraries it is no longer the issue of access, it is the navigation, relevance and efficient selection of the appropriate information sources. Much of the literature available has focused on the performance of retrieval and on service efficiency with less attention to the cognitive implication of the interaction on the information-rich digital environments.

Query rewriting and relevance assessment and synthesis take place in multiple sessions, leading to a strain on the mind and fatigue in decisions (Shah and

Bender, 2022; Koehler and Sauermann, 2024). This indicates that the definition of digital libraries can be expressed as cognitive-technical space of experience of information, which is an interaction between processes of information retrieval in the form of algorithms between the user's cognition and information. This Framing is a cognitive-technical framing that aligns digital libraries with the modern information behaviour literature which considers search as a judgement work in the situated context.

2.2 Digital Information Systems – Information overload

Arnold et al. (2023) and Shahrzadi et al. (2024) described information overload as a situation where the complexity of information flow exceeds the capability of cognitive processing of information users, minimizing the quality of the user's decisions and causing mental stress to the user. This view is given theoretical support of Cognitive Load Theory, which highlights the limited capacity of working memory.

Most of the previous studies view overload as negative, which is related to a decrease in understanding, decision making fatigue, and decreasing satisfaction (Hair and Alamer, 2022; Sarstedt et al., 2022). However, in a digital library setting, this kind of reading is being questioned because people not only seek out information, but looking at, comparing, synthesizing and evaluating multiple information sources are integral aspects to the information-seeking process.

Greater perceived overload in these settings could indicate how profoundly academics are engaged, as opposed to blatant system malfunction. Evaluative demands can be exacerbated by presenting a range of relevant contents and overload is a circumstantial cognitive response, which depends upon the complexity of the demand, user purposes and system design.

2.3 Information Filtering in Digital Libraries

Information filtering is widely known to be one of the fundamental processes in dealing with large amounts of information in digital libraries. The use of ranking algorithms, recommender systems, personalised retrieval or semantic search using AI is targeting the ranking of the relevant content and improving the speed of navigation (Khavidaki et al., 2023; Mitreva et al., 2026). The general trend in LIS research, oriented towards AI-assisted information discovery environments (Parmar et al., 2024), includes ranking algorithms, personalised retrieval, recommender system and AI-driven semantic search to rank the relevant content and improve the efficiency of navigation.

The effectiveness of filtering mechanisms in improving retrieval efficiency, reducing the exposure to irrelevant information and increasing user engagement is supported by considerable amount of empirical data (Sabiri et al., 2025; Aliwy et al., 2021). But the cognitive consequences of filtering are still not yet clearly theorized. more likely, Filtering can increase the requirement for evaluation as clustering of highly relevant alternatives, which can lead to comparing, prioritizing, and synthesizing more alternatives.

This is one of the major paradoxes in the investigation of digital libraries, as the systems that aim to reduce overload may be the same systems that aim to overload the cognitive system and get results of relevancy. For this reason, information filtering should not only be thought of as an optimization procedure but as a cognitive mediation procedure which affects the user's attention, judgement and knowledge formation. The conceptual framework on the use of overload as a potentially productive state of evaluation in the use of digital libraries is based on this paradox.

2.4 Satisfaction of users in digital retrieval environments

User satisfaction is also a basic indicator of the effectiveness of digital library, which indicates perceived usefulness, ease of use, system quality and information relevance (Misra et al., 2024). In an academic retrieval environment, there are accessibility, system responsiveness and quality of information retrieved which is a significant determinant of satisfaction.

Satisfaction is not only related to the properties of the system, but also to the mental work required for processing retrieved outputs. In information rich settings, users can compare, interpret and synthesise the different sources of information that are relevant. In this instance, perceived overload can mediate the overall usefulness of the system that is perceived by the users.

There's an increasing amount of evidence for dual relationships: too much cognitive load results in a loss of clarity and fatigue while too much of relevant material results in a sense of completeness, confidence and depth of knowledge. Moderate overload in the case of academic digital libraries can thus go hand in hand with positive satisfaction levels.

Although there are studies on the relationship between satisfaction and usability and between satisfaction and relevance in Digital Library (DL) setting, the relationship between the two is not well studied.

2.5 Research Gap

Despite the existing research conducted by previous scholars, who have contributed a lot of knowledge on digital libraries, information filtering and overload, there is a lack of empirical data on how the structural relationship between them can be related in a single explanatory model. Existing literature focuses primarily on filtering and reducing overload with limited evidence in real digital library environments.

Furthermore, relationship between overload and the satisfaction of the user is still hypothetically unclear. The classical position sees overload as a bad phenomenon, but the new evidence is that overload can go hand in hand with a positive attitude to usefulness of the system and a level of involvement in academic information settings.

To fill these gaps, this paper proposes an integrated structural model that intervene rates information filtering, perceived information overload and user satisfaction in digital library environment, followed by an empirical test of the model.

3. Conceptual Framework

The theoretical model of this research suggests that there is a structural interaction between information filtering, perceived information overload and user satisfaction in digital libraries. The framework is based on the Cognitive Load Theory and Information Behaviour Theory wherein the system-level filtering mechanisms have an influence on the cognitive processing experiences of the users and, consequently, on the evaluative outcomes of digital information usage.

What is new about the framework is the fact that perceived overload is an evaluative cognitive mechanism, and not a dysfunctional outcome variable.

The model suggests that mechanisms of information filtering like ranking algorithms and recommender systems and personalised retrieval have an impact on the user's information viewing and evaluation in relevance-rich search situations. Theorisation of these processes at the system level is assumed to help to create the perception of information overload by playing with the number, diversity, and assessment demands for the retrieved outputs.

Information perceived as overloaded is perceived as the mediating cognitive process where the filtering process impacts user satisfaction. So, user satisfaction is the process of general assessment of usefulness of the system, the relevance of the information, and retrieval ability in digital library environment.

In this respect, the framework provides:

- a direct line of information filtering to user satisfaction, and
- the perceived information overload taking an indirect route.

Such a combined route allows considering both the possibility of filtering enhancing satisfaction itself and the possibility that the impact of filtering is channelled, in the first place, via the experience of cognitive processing by users.

The proposed conceptual framework depicts the structural relationship between information filtering, perceived information overload and user satisfaction in digital library environment. As illustrated in Figure 1, perceived information overload is greatly affected by information filtering, and this information overload has a positive effect on user satisfaction. The direct link between information filtering and user satisfaction did not have a statistical significance.

4. Hypotheses Development

4.1 Information Filtering and Information Overload

The information filtering systems are intended to focus on important information and lessen the complexity of navigation. But filtering can also help to expose users to hundreds of highly relevant sources at the same time in a digital library environment and the user will need to compare, evaluate and synthesise competing materials. It may also increase cognitive work used in relevance judgement, as opposed to merely decreasing the informational load. In this

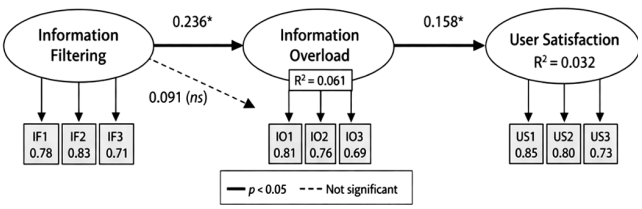

Fig. 1 — Structural model showing the relationships among information filtering, perceived information overload, and user satisfaction in digital library environments.

respect, filtering can result in cognitive demand as evaluative overload.

H1: Information filtering positively influences the perceived information overload in digital libraries.

4.2 Overabundance of Information and User Satisfaction

Though the concept of information overload is conventionally linked to negative cognitive effects, recent literature indicates that exposure to a variety of relevant information, in the context of academic digital setting, can reinforce the perceived usefulness and level of comprehension. Cognitive effort can refer to positive academic effort, rather than dysfunctional burden, per se.

H2: Perceived information overload is positively related to user satisfaction in using digital libraries.

4.3 Information Filtering and User Satisfaction

The purpose of information filtering is to improve the effectiveness of retrieval, to increase relevance, and to save from irrelevant search. By displaying more specific and useful information to users, filtering mechanisms can potentially enhance the usefulness of the system and facilitate more information-based decision making, thereby leading to greater satisfaction. But when evaluative cognitive processing of the users proves to be the crucial explanatory process, this direct effect can be eliminated.

H3: Information filtering has a positive effect on user satisfaction with digital libraries.

4.4 Mediating Role of Information Overload

Information filtering is a process that defines the way in which the digital library's products are organized, prioritized, and cognitively processed. Such filtering-based cognitive experience may be manifested as perceived information overload that in turn impacts the final evaluation of system usefulness and satisfaction outcome of the users.

H4: Information overload mediates the relationship between information filtering and user satisfaction.

5. Research Methodology

5.1 Research Design

The research design used in this study was quantitative which is cross-sectional as it was based on investigating the structural relationship between information filtering, information overload and user satisfaction in digital library environments. The approach was suitable since the research objective was to test the hypothesised relationships amongst the latent variables using statistical modelling.

This was descriptive as well as explanatory study. It was descriptive in its profiling of the demographic characteristics and digital library use of the subjects and explanatory in its testing of the hypothesized relationships of the structural model.

5.2 Population, Sampling, and Sample Size Justification

The target population consisted of digital library users with 390 used as the number of valid responses. This was the lowest value for the Partial Least Squares Structural Equation Modelling (PLS-SEM) like the 10-times rule and the statistical power levels stated in the literature (Hair et al., 2022).

Purposive sampling was used to make sure that the respondents had a prior experience in using digital libraries. This has contributed to the contextual relevance and construct validity but might not have contributed to generalizability of the results. The results obtained are then to be interpreted within the context of digitally active user groups.

5.3 Instrument Development and Measurement Scales

A structured questionnaire with two sections was used to collect data from the respondents

Demographic information (gender, age, duration of use and frequency of use of digital library). B: measurement items of the latent constructs.

In this paper, three constructs were operationalized:

i. Information Filtering (IF): perceived effectiveness of retrieval level of the system and information organisation.
ii. Information Overload (IO): perceived load of the brain and the inability to process the information retrieved.
iii. User Satisfaction (US): General opinion of the system and experience in terms of usability.

The constructs measures were carried out by multi-item reflective scales developed from previous research in the field of digital library, information system and cognitive load studies. Each one of them was measured on a 5-point Likert scale ranges (1 = Strongly Disagree to 5 = Strongly Agree). Face validity and contextual clarity of the instrument were reviewed and then the final administration was done. The questionnaire items were modified to match the digital library context and at the same time maintain their theoretical significance.

The scale items adopted for the constructs in this study were based on those of previous studies in digital

Table 1 — Measurement items for the study constructs

Construct	Code	Measurement Item	Source
Information Filtering (IF)	IF1	The digital library provides results in a well-structured and understandable format.	Adapted from Khalid *et al*. (2025); Khaydarova et al. (2026)
	IF2	The system is capable of ranking the most relevant information.	Adapted from Khavidaki *et al*. (2023)
	IF3	Search results are relevant to my information needs	Adapted from Zhang (2022); Kumar and Gupta (2022)
Information Overload (IO)	IO1	I experience overload from the information retrieved.	Adapted from Arnold et al. (2023); Shahrzadi *et al*. (2024)
	IO2	The information is difficult to process and understand.	Adapted from Eppler and Mengis (2004); Shahrzadi *et al*. (2024)
	IO3	The system requires substantial mental effort to analyse the results.	Adapted from Sweller (1988); Hair and Alamer (2022)
User Satisfaction (US)	US1	Overall, I am content with the digital library.	Adapted from DeLone and McLean (2003)
	US2	This system is effective in addressing my information needs.	Adapted from Misra *et al*. (2023)
	US3	The online library is applicable in my academic life.	Adapted from Lu and Lin (2024); Kumar and Gupta (2022)

libraries, information systems and cognitive load studies. Table 1 shows the information filtering items, information overload items, and user satisfaction items used in the study and their corresponding sources.

5.4 Data Analysis Technique

Smart PLS 4 was used to analyze data using the Partial Least Squares Structural Equation Modelling (PLS-SEM). This technique is appropriate in predictive analysis, latent construct modelling and mediation testing in structural models. The guidelines of established PLS-SEM (Hair et al., 2022) were followed.

5.5 Data Screening and Preliminary Analysis

The dataset was checked for quality and consistency prior to estimation of the model. None of the substantial missing values were found, no severe outliers were identified, nor were any abnormal response patterns identified. To determine common method bias (CMB), Harman single factor test was done. In addition, the results indicated that the maximum variances were not explained by any factors, thus there was not significant problem of common methods bias in the data set. The values of Variance Inflation Factor (VIF) were also checked to eliminate the issue of collinearity in the structural model. It was these steps that qualified the appropriateness of data to structural modelling.

5.6 Measurement Model Assessment

Source: Adapted from Hair, J. F., Christian M. Ringle, & Marko Sarstedt. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (Third Edition). SAGE Publications.

Using bootstrapping, the statistical significance of the structural paths was estimated and was used to provide strong inference during the process of hypothesis testing (Table 2).

5.7 Mediation Analysis

The analysis was carried out to determine the indirect impact of information filtering on user satisfaction by information overload. Bootstrapped indirect effects and significant testing of the indirect path were used to determine the mediation effect.

5.8 Model Specification

The structural relationships that were to be tested in the current study were:

Information Filtering --> Information overload.

Information overload/User satisfaction.

Information filtering → satisfactory use.

The mediating process was identified as:

Filtering information → Information overload → User satisfaction

This model is a process model which is a relation between system level mechanisms of filtering and users' experience and outcome of satisfaction in Digital Library environments.

5.9 Ethical Considerations

The study was voluntary and the respondents were assured that their answers would be anonymous and confidential and could not be identified. The ethics procedure was done in accordance with institution based

Table 2 — Measurement Model and Structural Model Assessment Criteria in PLS-SEM

Assessment Criterion	Threshold/Criteria	Purpose
Indicator Reliability	Factor loadings ≥ 0.70 (≥ 0.60 accepted where theoretically justified)	To assess the reliability and adequacy of individual measurement items
Internal Consistency Reliability	Cronbach's Alpha ≥ 0.70	To evaluate construct reliability and consistency among indicators
	Composite Reliability (CR) ≥ 0.70	To confirm the overall internal consistency of latent constructs
Convergent Validity	Average Variance Extracted (AVE) ≥ 0.50	To determine the extent to which indicators converge to measure the same construct
Discriminant Validity	Heterotrait–Monotrait Ratio (HTMT) < 0.85	To ensure that constructs are empirically distinct from one another
Structural Model Assessment	Path coefficients (β)	To examine the strength and direction of hypothesised relationships
	t-values and p-values (Bootstrapping)	To determine the statistical significance of structural relationships
	Coefficient of Determination (R^2)	To assess the explanatory power of endogenous constructs

voluntary social science research survey and informed consent was obtained from all the respondents.

6. Results

For the analysis, there were 390 valid responses. The proportion of genders was quite even with 53.6 percent of the respondents being male (n = 209) and 46.4 percent being female (n = 181). The age profile showed broad representation across user groups, with the 18–25 years category (21.5%) forming the largest segment, followed closely by 36–45 years (21.3%), 46–55 years (21.0%), 26–35 years (19.2%), and 56 years and above (16.9%).

Respondents were also very positively oriented towards digital libraries. Almost a third (29.0% said that they had been using digital libraries a few times weekly, whereas 24.6% said that they did so every day. The weekly user population was 22.6% and the occasional use was 23.8%. In general, the sample distribution ensures that the sample was mostly comprised of active digital library users, and thus it was suitable to investigate the level of perception of filtering and overload, and user satisfaction.

Tables 3, 4 and 5 show the demographic data and digital library usage of the respondents who participated in the study. The tables present gender distribution, age categories and frequency of digital library use of the respondents.

Table 3 — Gender Distribution

Gender	Frequency	Percentage
Male	209	53.6
Female	181	46.4
Total	390	100.0

Table 4 — Age Distribution

Age Group	Frequency	Percentage
18–25	84	21.5
26–35	75	19.2
36–45	83	21.3
46–55	82	21.0
56 and above	66	16.9
Total	390	100.0

Table 5 — Digital Library Usage Frequency

Usage Frequency	Frequency	Percentage
Daily	96	24.6
Several times a week	113	29.0
Weekly	88	22.6
Occasionally	93	23.8
Total	390	100.0

6.1 Measurement Model Evaluation

An acceptable reliability and convergent validity of the measurement model was found. All the indicator loadings were within the acceptable level of reliability of items; between 0.69 and 0.85. The composite reliability coefficients were between 0.84 and 0.88, which is higher than the recommended 0.70, and AVE (0.63-0.71) were higher than the acceptable 0.50 level. The values of Cronbach alpha were 0.72 to 0.79, which is acceptable internal consistency of all constructs.

Indicator loadings, Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) were used to measure the reliability and convergent validity of the study's constructs. The reliability and the convergent validity outcomes for the constructs in the measurement model are provided in Table 6.

Table 6 — Reliability and convergent validity of the study constructs.

Construct	Items	Loadings	Cronbach's Alpha	CR	AVE	Interpretation
Information Filtering (IF)	IF1–IF3	0.71–0.83	0.76	0.86	0.67	Strong
Information Overload (IO)	IO1–IO3	0.69–0.81	0.72	0.84	0.63	Acceptable
User Satisfaction (US)	US1–US3	0.73–0.85	0.79	0.88	0.71	Strong

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to evaluate measurement and structural models. Figure 2 shows the standardised indicator loadings for the measurement model and the structural model with the hypothesised relations between information filtering, information overload and user satisfaction.

6.2 Discriminant Validity Assessment

The Heterotrait–Monotrait Ratio (HTMT) was used to examine the discriminant validity. As shown in Table 7 all the HTMT were below 0.85, the proposed threshold value and ranged between 0.31 and 0.48, showing good discriminant validity between the various constructs studied in this research.

6.3 Structural Model Results

Path coefficients, t-values, and p-values from bootstrapping analysis were used to assess the structural model. Table 8 shows the findings from the hypothesis testing of the proposed structural relationships between the constructs in the study. The results show that Information Filtering ($\beta = 0.236$, $p < 0.001$) contributed significantly in a positive way to Information Overload, supporting H1. likewise, Information Overload was significantly and positively related to User Satisfaction ($\beta = 0.158$, $p = 0.003$), thus supporting H2. The direct path of Information Filtering to User Satisfaction, however, was not statistically significant ($\beta = 0.091$, $p = 0.059$) which also resulted in the rejection of H3.

The experience of cognitive processing is mediated by information overload which is a major between the information filtering and satisfaction of the users indicated in Figure 3, which directly or indirectly affects the satisfaction of the users. Through the mediation analysis, the indirect effect of information filtering through information overload to user satisfaction was explored. Results show that information overload has a significant mediating effect on the relationship between information filtering and user satisfaction as illustrated in Figure 3 and the direct link between information filtering and user satisfaction is statistically non-significant.

Table 7 — Discriminant validity assessment using the HTMT criterion.

Construct	IF	IO	US
IF	—	0.48	0.36
IO	0.48	—	0.31
US	0.36	0.31	—

Table 8 — Path coefficients and hypothesis testing results.

Hypothesis	Path	β	t-value	p-value	Decision
H1	IF → IO	0.236	5.12	<0.001	Supported
H2	IO → US	0.158	2.98	0.003	Supported
H3	IF → US	0.091	1.89	0.059	Not Supported

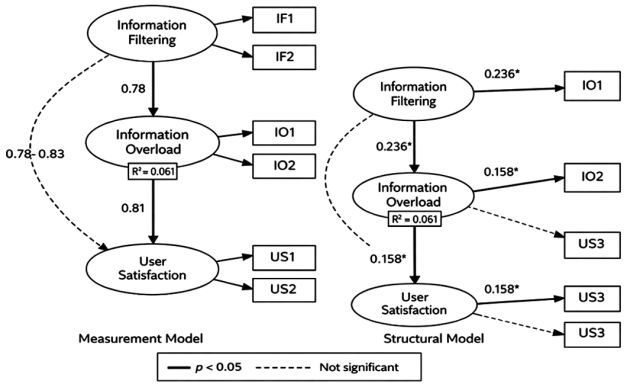

Fig. 2 — Measurement and structural models with standardised loadings and path coefficients.

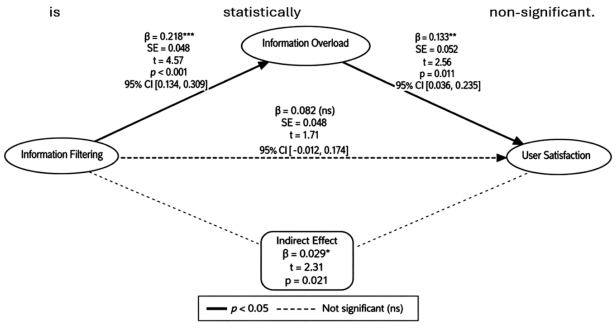

Fig. 3 — Bootstrapping results show the mediating effect of information overload on the relationship between information filtering and user satisfaction.

6.4 Coefficient of Determination (R^2)

To evaluate the explanations of the endogenous constructs within the structural model, the coefficient of determination (R^2) has been used. According to Table 9, the R^2 of Information Overload was 0.061

Table 9 — Coefficient of determination (R^2) of the endogenous constructs.

Variable	R^2	Interpretation
Information Overload	0.061	Weak–Moderate
User Satisfaction	0.032	Weak

Table 10 — Indirect effect and mediation analysis results.

Path	Indirect Effect	t-value	p-value	Result
IF → IO → US	0.037	2.74	0.006	Significant

and User Satisfaction recorded an R2 of 0.032 which was considered a weak explanatory power. The relatively low explanatory power might stem from user-centred studies of information behaviour commonly reporting such values for the satisfaction outcome, which might be explained by multiple contextual and situational factors that do not form part of the constructs in the present model.

6.5 Mediation Analysis

To investigate the indirect effect of Information Filtering on User Satisfaction via Information Overload, the mediation analysis was performed. The indirect effect was statistically significant and positive ($\beta = 0.037$, $p = 0.006$), thus showing that Information Overload significantly mediates the relationship between Information Filtering and User Satisfaction as shown in Table 10. In addition, the presence of significant indirect effect despite the non-significant direct effect mentioned previously shows the existence of complete mediation and hence justifies H4.

7. Discussion

The study examined the relationship between variables, namely information filtering and perceived information overload and user satisfaction in digital library environment providing empirical evidence for the relationship between system level retrieval mechanism and user cognition. The findings add to the literature in Digital libraries and Information Behaviour Studies through redefining the notion of system efficacy to one that is more process-oriented and one that focuses on user experience.

There is positive correlation between information filtering and perceived information overload, suggesting that information filtering is not directly correlated with reduced information overload. Instead, there will be multiple retrieval systems where users can access multiple (highly relevant) sources that will require synthesizing, prioritizing and comparing to determine which is most relevant. This confirms the opinion that overload in digital library environments is not only determined by the amount of information but also by the judgmental task that is posed by the complexity of relevance (Gunarathna, 2024; Roy *et al*., 2024; Shahrzadi et al., 2024).

The results challenge the notion of overload in digital library research as more than just a state of too much and begin to define overload as an effective state of assessment that results from a "relevancy-rich retrieval situation. This is an extension of the main contribution made in this manuscript which shows that such evaluative overload mediates the linkage between information filtering and user satisfaction completely.

The theoretical change goes beyond the volume-based interpretations of overload in conceptualising filtering to be a cognitive mediation process reconfiguring and not eradicating complexity. This overload may be an engaged sense-making activity by users in academic digital spaces, rather than some inefficiency in the system, in which users engage in critical comparison and knowledge synthesis.

This meaning is also reinforced by the fact that perceived overload had a positive correlation with user satisfaction. Delivering various types of information sources, both pertinent and relevant, may enhance perceived usefulness, confidence and depth of understanding in digital library environment. This reflects the information behaviour perspective of information searching which looks at information searching as an iterative, evaluative and contextual process rather than a linear one.

The total mediation effect indicates that the effect of filtering on user satisfaction is mediated by the cognitive experience of processing the information by the user and not by a system-effect. This is why perceived overload is the key element of the central role of cognitive mechanisms linking retrieval architecture and experiential outcomes. The result confirmed the digital library theory which theorizes that the features in the system affect satisfaction and are process orientated in nature.

The results are coherent with the perspective of the digital library interaction, as it has been cognitively located in the filtering and in the overload as mediators of the evaluative processing needs, and in the satisfaction as arising from a relevant interaction in the digital library with outputs of relevance. The paper thus also broadens the theory of Digital Library relevance optimisation to cognitively situated evaluative interaction.

8. Implication for Digital Library Research and Practice

8.1 Practical Implications

The results indicate that the development of digital libraries should not be centered on the conventional filtering techniques that are based mainly on minimizing information volumes. Instead, cognitive supportive retrieval functions such as clustering, summarisation, guided exploration, relevance grouping and visual comparison interface should be brought into the systems. These functions can assist users to make interpretations across various relevant options, enhance evaluative judgement, and promote academic sense-making in academic settings that are information-rich.

For the designers of digital libraries, however, it is not efficient architectures that matter, but systems that support cognition, which offer opportunities for comparison, synthesis, and decision making. The results are relevant for academic libraries in the development of cognitively assistive discovery interfaces for better, deeper, scholarly decision-making than just relevance ranking.

8.2 Theoretical Implications

The research is an addition to the area of information overload in the context of digital-based information overload to present an improved conceptualisation. Findings indicate that overload is not an unwanted cognitive outcome, however, it may coincide with a greater sense of satisfaction, if the users feel that the richness of the relevance and meaningful involvement are offered.

The research therefore extends the digital library theory, by offering overload as a situational mental state driven by the system design, the user's intention and the evaluative requirements of the tasks. The re-conceptualisation shifts the overload perspective to a deficit-based perspective to a productive evaluative situation that is generated in relevance-rich retrieval contexts and does so in this way, offers a more nuanced account of user experience in contemporary digital library systems.

This meaning resonates with the recent evidence of ALIS that reveal that the quality of relevance and perceived usefulness, rather than just the size of the collection, are more important to users in the digital library setting (Gunarathna, 2024).

9. Conclusion

The paper also looked at the relationship between information filtering and perceived information overload and user satisfaction in digital libraries. The results show that filtering does not have a direct effect on satisfaction, but its effect is mediated by the cognitive experience of perceived overload. Interestingly, overload was also found to have a positive effect on satisfaction; as such, it should be noted that exposure to information that was relevant and easily understandable may explain the more profound scholarly involvement rather than simply the creation of a cognitive load.

The research contributes to digital library research by showing that overload is a mediated mental state that is dictated by retrieval design and evaluative requirements and is not the dysfunctional result of an abundance of information. This process-based approach will support the existing information behaviour and digital library theories, by preventing the communication process between system design and cognition in users.

The next generation digital library architecture should therefore be designed to provide efficient access to the appropriate information, but also support the evaluative awareness of the users, if it is to serve in the context of the relevance-rich scholarly environment.

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