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Effects of Personalized Algorithmic Sorting on Information Seeking Success Among E-Learners With Diverse Prior Knowledge

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Abstract

This research examines the influence of individualized algorithmic sorting on the information-seeking effectiveness of e-learners with various levels of prior knowledge in Indian institutions of higher learning. The study also examinedthe effectiveness of adaptive ranking in facilitating retrieval, and also look at whether prior knowledge buffers this relationship. The quasi-experimental design took place in a group of 180 university students who were divided into personalized and non-personalized search interface groups. A structured pre-test was used to divide the participants into low, medium, and high rior knowledge. The success of Information seeking was assessed by the accuracy of retrieval, relevance score, time of completing a task, and satisfaction of the user. The analysis involved the use of two-way ANOVA and moderation regression analysis. Findings have shown that individual algorithmic sorting contributes greatly to the success of general information search ($F = 12.84$, $p < 0.01$). A significant main effect is also present in the case of prior knowledge ($F = 18.67$, $p < 0.01$). The ANOVA ($F = 6.42$, $p < 0.05$) interaction effect is statistically significant with the aid of moderation regression coefficients ($\beta = 0.29$, $p < 0.05$) and proves that prior knowledge mediates the relation between the two variables under consideration, i. e., algorithmic sorting and search results. Personalization especially helps low prior knowledge learners achieve a better relevance identification, and also reduced search time, whereas high prior knowledge learners are good in either interface condition. The results are favorable to the implementation of adaptive information retrieval systems in digital libraries and online learning platforms to guarantee equal and effective access to Information in the Indian higher education setting. The study provides empirical evidence to the Information Behavior and Information Retrieval research by showing the interaction of system-level personalization with cognitive characteristics. It also includes useful ideas to use when constructing inclusive digital classrooms, which can use personalized algorithmic ranking without restricting the exploratory behavior of more knowledgeable learners.

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Introduction

The high growth in the digital learning infrastructures in India has transformed the way learners search, access, and interact with academic Information.[1, 13] Digital libraries, learning management systems, and AI-enhanced discovery tools are now part of higher education curricula in universities and other institutions of higher learning.[2, 14] The use of an algorithmic sorting as a fundamental process of search results organization, the suggestion of resources, and the filtering of extensive information spaces has become a central feature within these platforms.[12] In place of the straightforward, document-neutral, or purely chronological display of documents, most modern systems are based on intricate ranking capabilities that add relevance indicators, click-through behaviors, and inferred user preferences. Such a change poses significant questions to the discipline of Information Behavior and digital library studies: beyond convenience and engagement, what impact do such algorithmic choices have on the capacity of learners to effectively identify, analyze, and utilize Information to complete academic services?

The study of Information seeking has highlighted that an interaction between the system design and user characteristics is what leads to the development of effective search behavior. Information behavior and information seeking processes classic models reveal that people do not just retrieve Information; they go through the phases of uncertainty, exploration, and focus collection influenced by the cognitive, affective, and contextual factors. Algorithms sorting in online academic settings interfere with exactly these areas by determining what information people can see at first, what sources seem the most authoritative, and how much effort it takes to leave the highest-ranking results. Learners are, simultaneously, very different in terms of their familiarity with the domain and search skills. Prior knowledgein a specific subject facilitates the formulation of queries, relevance assessment, and evaluation of competing sources, and learners with stronger prior knowledge may apply more surface features like ranking position or interface labels. However, the current research has failed to adequately explain the interactions of such cognitive differences with the personalization facilities integrated into the search interfaces.

Such interaction is particularly relevant in the Indian context of higher education, considering the heterogeneity of the language background, schooling, and exposure to digital technologies. Although national and institutional programs have increased access to digital repositories and e-learning communication, little or no empirical research on the positive or unforeseen limitations to the success of Information seeking by learners with varying levels of prior knowledge is available on whether personalized algorithmic sorting positively or negatively impacts research outcomes.[3, 15] The research on personalization in education is mostly based on recommendation accuracy or measures of engagement instead of composite measures, which would combine retrieval accuracy, relevance, efficiency, and satisfaction in genuine academic activities.[4, 9] In addition, prior knowledge moderation is seldom explicitly tested in quasi-experimental designs and interaction-based statistical models. This paper fills these gaps by exploring the impacts of personalized and non-personalized sorting on the success of Information seeking among Indian e-learners and exploring whether the relationship between personalized and non-personalized sorting and prior knowledge is moderated. This is aimed at producing evidence that can guide the design of effective and equitable digital libraries and e-learning systems that will suit different learner populations.[5, 16]

Research Hypotheses

- H1: E-learners find greater success in the information-seeking process with personalized as compared to non-personalized algorithmic sorting.

- H2: The success in the Information seeking among learners with high prior knowledge is more than the success in the Information seeking of learners with low prior knowledge, regardless of sorting conditions.
- H3: Prior knowledge determines the influence of algorithmic sorting on information-seeking success, in the sense that the positive influence of personalized sorting is greater in the case of lower prior knowledge learners.

Key Contributions

1. Offers empirical data concerning the effect of personalized algorithmic sorting in an Indian e-learning scenario.
2. Proves the moderating effect of prior knowledge in determining the success of Information seeking.
3. Provides viable design solutions to adaptive digital library and information retrieval systems.

The rest of the paper is organized in the following way. Section 2 provides the literature review of the Information-seeking behavior and personalized retrieval systems, and the Prior knowledgeframeworks, and formulates the research hypotheses. Section 3 provides the methodology of the research, research design, sampling, measurement tools, and statistical procedures. Section 4 gives the empirical findings and the test of the hypothesis. Section 5 identifies theoretical and practical implications for information systems and digital libraries. Section 6 summarizes the study and provides future research directions.

Literature Review and Theoretical Framework

Information access and retrieval practices in higher education have been changed enormously by the growth of digital learning environments.[18, 20] A growing number of academic search platforms, digital repositories, and learning management systems have made use of algorithmic sorting mechanisms in order to present and organize Information.[6, 10] Via these systems, content is ranked based on the relevance indicators that include: matching keywords by users, user history, user engagement history, and context. Nowadays, with the development of artificial intelligence and the analysis of data, individual algorithmic sorting turned out to be the key aspect in information systems. These systems will help users achieve better retrieval efficiency, less cognitive effort, and better user satisfaction by providing personalized search results based on user profiles. The real effect of personalization on success in learning-oriented search, however, needs a more profound conceptual and empirical study.[7, 19]

The Information-seeking behavior theory emphasizes that an effective search is related to system features and the cognition of users. The digital space offers orderly interfaces, algorithm ranking, and recommendation systems that inform the interaction of users. Meanwhile, these differences between individuals, including digital literacy, motivation, and Prior knowledge, influence the interpretation of search results by users. Information seeking is not a mechanical process of finding results, and the evaluation, comparison, and integration of retrieved Information are involved in the Information seeking. In the education world, students have to analyze credibility, relevancy, and accuracy before they can utilize Information in the process of learning.[8] Thus, cognitive ability and technological design act concurrently to determine the search performance.

Individualized algorithmic sorting has an effect on the visibility and perceived significance of Information. Top-ranked results are usually given more attention by the users who believe that they are more relevant. Individualization can thus ease the process of finding appropriate resources and save time on search. This may also be quite useful in large collections of digital materials where information overload is the rule. Nevertheless, personalization can also limit or narrow access to other views and inhibit exploratory search behavior.[17, 21] The importance of its effectiveness relies mainly on the way the Information of the rankings is processed by the users, and the degree to which the presented results are critically assessed.

Previous experiences are important in such a process. Students with more familiarity in the domain have a more conceptual framework that aids in query formulation, evaluation of sources, and integration of the content. They will be more doubtful about the arrangement of order and evaluate the quality of Information on their own. By contrast, unfamiliar learners are likely to rely heavily on system-generated indications like ranking position or label of recommendations. Personalized sorting can be used as cognitive support with these learners, as it emphasizes more contextually-appropriate resources. The existence of prior knowledge is therefore anticipated to respond to the connection between algorithmic sorting and Information-seeking success.

Those indicators that can be used to evaluate information-seeking success can be both objective and subjective. Objective measures are retrieval accuracy, relevance of sources that have been selected, and the time required to complete the search. The subjective ones are the perceived usefulness and satisfaction with the search experience. Proper information systems are expected to increase effectiveness as well as the quality of results. Including system-based and human-based views, the theoretical background of the current research suggests that individualized algorithmic sorting has a direct impact on the success of the search process, prior knowledge has a direct impact on performance, and the combination of the two variables defines the effectiveness of search-based digital information retrieval.

Methodology

Research Design

The research design that was used in this study was a quasi-experimental type of research to investigate the impact of personalized algorithmic sorting in determining the success of Information seeking among different levels of e-learners with prior knowledge. There are two search interface conditions: (1) customized algorithmic sorting, (2) no customization sorting. The customized interface prioritized the results with adaptive signals in accordance with the simulated user profiles, whereas the non-personalized one prioritized the results with the neutral relevance-based ranking and without custom consideration to the user. To reduce selection bias, the participants were randomly divided into conditions.

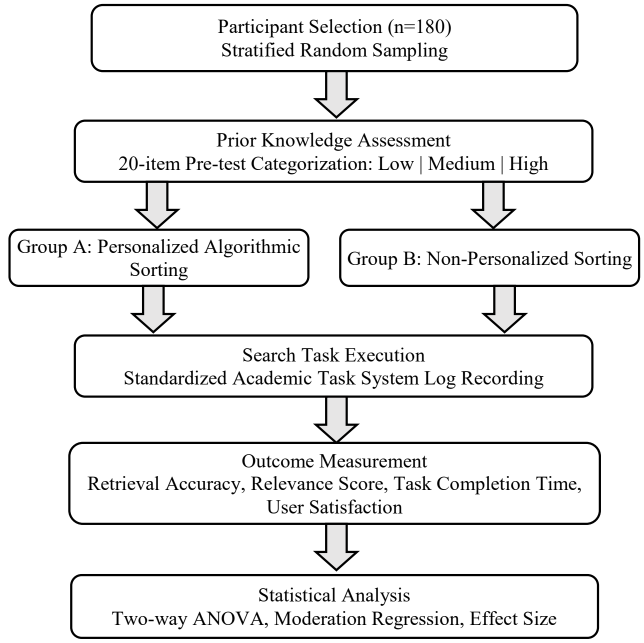

Fig. 1: Experimental Workflow for Assessing the Impact of Personalized Algorithmic Sorting on Information Seeking Success

The structured quasi-experimental design that is adopted in the study is shown in Figure 1. The sample size of 180 subjects was chosen by means of stratified random sampling and initially assessed with the help of a 20-item pre-test to identify the level of prior knowledge, which was grouped into low, medium, and high levels. The participants were then allocated to either of two experimental conditions, which are Group A (personalized algorithmic sorting) and Group B (non-personalized sorting). An academic search task that was a standardized search was done on both groups, with system logs taken. The success of Information seeking was measured with the help of retrieval accuracy, relevance score, task completion time, and user satisfaction. Two-way ANOVA, moderation regression, and effect size estimation were used to analyze the collected data in order to test main and interaction effects.

Participants and Sampling

The research was done on undergraduates and postgraduate students in institutions of higher learning. Stratified random sampling was used to ensure that there is representation in the various fields of study and levels of study. The number of learners who took part in the experiment was 180. The knowledge of the subject was assessed by the use of a structured 20-item pre-test that aimed at testing familiarity with the domains of the tasks to be performed during the assigned search activities. On the basis of percentile distribution, participants were divided into low, medium, and high prior knowledge groups. The sample size was deemed to be statistically sufficient to identify the presence of moderate-sized effects at a significance level of 0.05 with adequate statistical power.

Variables and Measurement

The independent variable in this research was the kind of algorithmic sorting that was used in the search interface, and that was either personalized or non-personalized. The moderating factor was the level of prior knowledge, which was established by pre-tests. Information seeking success was the dependent variable, which was measured with the help of various objective and subjective indicators. The level of retrieval accuracy was determined by the sources that were correctly recognized during the task. The relevance score was identified by the expert guidance of chosen documents. System logs were used to measure efficiency by recording the time spent completing tasks. The survey was done on a five-point Likert scale to gauge the level of user satisfaction. These indicators were standardized and combined to come up with a composite Information Seeking Success Index.

Data Collection Procedure and Data Analysis Techniques

The participants were first required to complete the prior knowledge assessment under supervised conditions. They were then categorized and offered, based on their field of study, a standardized academic search task and given the two search interface conditions to search through. The digital interface automatically registered behavioral measures such as navigation behavior, click behavior, and time taken to accomplish the task. Participants were asked to answer a structured satisfaction questionnaire after completing the search activity. Informed consent was taken beforehand by all the participants, and the process was standardized to provide uniformity in the experimental groups.

Statistical software was used to analyze the data in order to examine the direct and moderating effects. Descriptive statistics were initially calculated in order to describe differences in performance across groups. The main effects of the algorithmic sorting and prior knowledge, and their interaction effect, were tested by the use of two-way analysis of variance. To further confirm the interaction relationship, a moderation regression analysis was carried out. Effect sizes were calculated using eta squared and Cohen's f-squared to determine the magnitude of observed effects. Reliability analysis of the satisfaction scale yielded a Cronbach's alpha value of 0.83, indicating acceptable internal consistency.

Validity and Reliability

Experts were also involved to review search tasks and measurement instruments to guarantee content validity. Factor analysis was used as a construct validity to analyze survey responses. Internal validity was enhanced by procedural consistency, random assignment, and controlled conditions of tasks. Both objective performance measures and subjective measures have helped to increase the reliability and strength of the research design.

Results and Analysis

Descriptive Analysis

Calculation of descriptive statistics was performed to test the difference in the Information-seeking success in the conditions of the experiments and the level of prior knowledge. The individual form of sorting group showed greater overall performance in contrast to the non-personalized group, and learners who were better informed in the first place performed better, as indicated in Table 1. The largest absolute change in the case of personalization was for the low prior knowledge, and this implies that the adaptive ranking is especially beneficial to those learners who have less familiarity with the domain.

Composite Information Seeking Success Index (ISS)

In order to pool the four measures of Information seeking success: retrieval accuracy, relevance score,

Table 1: Descriptive Statistics of Information Seeking Success

Group Condition	Prior Knowledge	Mean Score	SD
Personalized	Low	73.85	7.92
Personalized	Medium	78.64	8.10
Personalized	High	82.71	7.48
Non-Personalized	Low	65.12	8.43
Non-Personalized	Medium	71.72	8.95
Non-Personalized	High	78.21	7.88

time to complete a task, and user satisfaction, a composite Information Seeking Success Index (ISS) was determined by each participant as illustrated in equation (1):

$$ISS_i = \frac{(Z_{Accuracy,i} + Z_{Relevance,i} - Z_{Time,i} + Z_{Satisfaction,i})}{4} \quad (1)$$

Main Effects of Algorithmic Sorting and Prior Knowledge

There was a two-way ANOVA that was used to test the main and interaction effects of algorithmic sorting (personalized vs. non-personalized) and prior knowledge (low, medium, high) on the Information Seeking Success Index (ISS). The results showed that the main effect of the algorithmic sorting was statistically significant, $F(1,174) = 12.84$, $p < 0.01$, and the eta squared of about 0.07, which corresponds to a medium effect size based on traditional standards. This implies that approximately 7 percent of the difference in ISS can be attributed to the presence of a personalized or non-personalized search interface in the hands of the learners.

The main effect of the prior knowledge was also significant, $F(2,174) = 18.67$, $p < 0.01$, with =0.10, which is also a medium effect. This suggests that variations in the background knowledge explain about 10% of the Information-seeking success, with high background knowledge showing superior performance in the different conditions. The correlation between algorithmic sorting and prior knowledge was found to be statistically significant, $F(2,174) = 6.42, p < 0.05$, and with 64) =0.07, which again represents a medium effect. These findings combined prove that information-seeking success is influenced by both system design and cognitive properties.

Where necessary, post-hoc comparisons (e.g., Tukey HSD) may be reported to demonstrate the pair-wise differences between prior knowledge groups in each of the sorting conditions, especially to indicate the greater gains of low prior knowledge learners.

Table 2 presents the two-way ANOVA results for the main and interaction effects of algorithmic sorting and prior knowledge on the Information Seeking Success Index (ISS).

ANOVA F-Value

The F-value for each main and interaction effect was calculated using the standard ANOVA equation (2)

$$F = \frac{MS_{Effect}}{MS_{Error}} \quad (2)$$

Interaction Effect and Moderation Analysis

The moderation regression analysis was done to further investigate the interaction between prior knowledge and algorithmic sorting. The model revealed that algorithmic sorting (=0.34, $p < 0.01$) and prior knowledge (=0.41, $p < 0.01$) had a significant positive influence on ISS, and the interaction value was significant (=0.29, $p < 0.05$; =0.38). These findings are congruent with the findings of ANOVA and suggest that the joint effect of sorting type and prior knowledge accounts for a significant amount of variance in the success of Information seeking, which supports the

Table 2: Two-Way ANOVA Results

Source of Variation	SS	df	MS	F	p-value
Algorithmic Sorting	842.61	1	842.61	12.84	<0.01
Prior Knowledge	1224.30	2	612.15	18.67	<0.01
Sorting × Prior Knowledge	421.52	2	210.76	6.42	<0.05
Error	11420.6	174	65.63	-	

Table 3: Moderation Regression Results

Variable	β	t-value	p-value
Algorithmic Sorting	0.34	3.89	<0.01
Prior Knowledge	0.41	4.72	<0.01
Sorting × Prior Knowledge	0.29	2.61	<0.05

R^2 = 0.38

conclusion of a medium-sized effect.

The moderation regression model, as presented in Table 3, also summarizes the main effect of algorithmic sorting and prior knowledge, and their interaction term, predicting ISS.

Moderation Regression Formula:

To test the moderating influence of prior knowledge on the connection between the algorithmic sorting and the achievement of Information seeking, the next regression model was approximated as presented in equation (3):

$$ISS_i = \beta_0 + \beta_1(Sorting_i) + \beta_2(PriorKnowledge_i) + \beta_3(Sorting_i \times PriorKnowledge_i) + \epsilon_i \quad (3)$$

Interpretation of Findings

The findings show that algorithmic sorting with no personalization hinders the success of Information seeking in an online academic setting. The strong key effects verify that the technological intervention and cognitive background have an independent impact on the search effect. More to the point, the moderation effect points out that adaptive ranking systems are more supportive of learners with less familiarity with the domain. Such results point to the fact that personalized retrieval mechanisms can also be used as compensatory ones, lowering cognitive load and pointing less experienced learners to the appropriate Information. Meanwhile, the medium effect identified in the case of high prior knowledge learners recommends that personalization is to be traded off with the mechanisms that promote exploratory and critical search behavior.

Figure 2 shows the interaction effect of the algorithmic sorting and prior knowledge on the success of Information seeking among the e-learners. The graph is a comparison of individualized algorithmic sorting (solid line) versus non-personalized sorting (dashed line) under the conditions of low, medium, and high levels of prior knowledge. Personalized sorting line reveals the highest enhancement of the success of Information seeking in low prior knowledge learners, which suggests that adaptive ranking receives a lot of support for lower-experienced learners. The performance difference declines with the degree of prior knowledge, with both curves approaching the high level of prior knowledge, indicating that high domain knowledge learners gain less benefit in personalization. Altogether, this number proves that algorithmic sorting influences the search performance differently in the case of Prior knowledge, which explains the

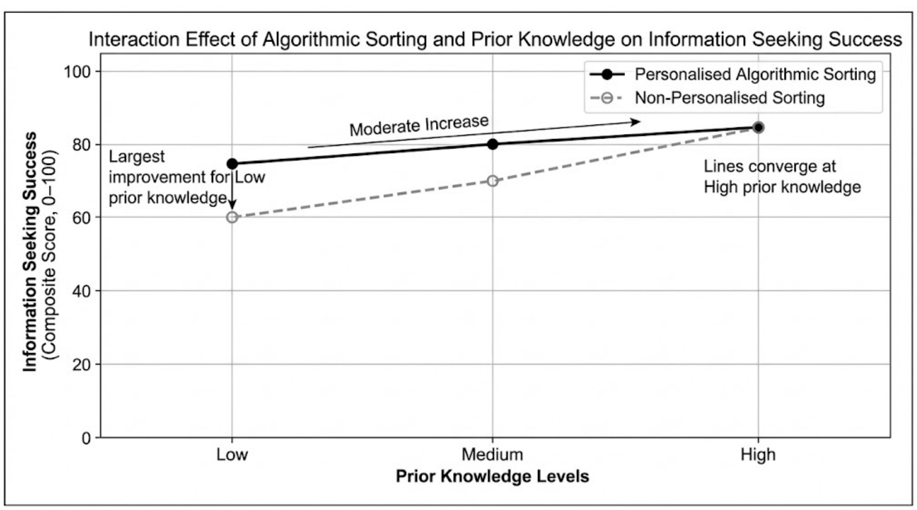

Fig. 2: Interaction Effect of Algorithmic Sorting and Prior Knowledge on Information Seeking Success.

role of adaptive information search systems in the broad group of learners.

Overall Interpretation

The results confirm the effectiveness of individual algorithmic sorting in boosting the success of Information seeking. Prior knowledge also has an independent effect on performance, and the substantial interaction attests to the effect that personalization improves the performance of low prior knowledge learners in a more significant way. The findings demonstrate the role of an adaptive ranking system in narrowing down the knowledge gap and enhancing efficiency in retrieval in a digital academic setting.

Discussion

The results obtained during this research can be regarded as strong confirmation of the first hypothesis (H1), according to which it was supposed that personalized algorithmic sorting would meaningfully contribute to the success of Information seeking in comparison to non-personalized sorting. The main effect of algorithmic sorting is significant, and the one of medium size (=0.07) shows that the adaptive ranking mechanisms have a meaningful positive impact on the ability of learners to find the Information they need and accomplish search tasks more effectively. These findings support the view that information behavior research advocates information interfaces as systems that may be designed to reduce cognitive load and enable simpler search processes in online contexts by means of interface design and ranking strategies. When applied to Indian higher education, in which the size of digital collections is huge, and they are heterogeneous, the indications that personalization promotes more successful composite Information seeking are that adaptive search interfaces can have a substantial role in facilitating the academic work done by learners.

The results also support the second hypothesis (H2), which concluded that prior knowledge would positively influence Information-seeking success and would be independent. The primary influence of prior knowledge, having a medium-sized effect (= 0.10), demonstrates that when familiar with the domain, learners are always successful in both personalized and non-personalized conditions. This is in line with well-known information-seeking models, which have placed stress on the relevance of cognitive structures in the formulation of queries, relevance judgments, and the integration of the retrieved Information. High prior knowledge learners seem capable of remedying the lack of personalization using their conceptual knowledge and evaluative capabilities, whereas low prior knowledge learners are more susceptible to the sequencing and presentation of Information. Such tendencies highlight the importance of involving learner cognition as one of the key influencing factors in the design of the digital system, instead of considering all users as the same.

Both the significant interaction term in the two-way ANOVA and the significant interaction coefficient in the moderation regression model ($\beta = 0.29$, $p < 0.05$) serve to confirm the third hypothesis (H3) that prior knowledge would moderate the relationship between algorithmic sorting and Information seeking success. The new medium-sized effect implies that not all learners gain equally from personalization, but rather the effect is a compensatory mechanism that provides the most benefit to those who have low prior knowledge. Individual sorting, to these learners, enhances the identification of relevance and saves time, making the performance difference between them and their higher knowledge counterparts smaller. In the case of highly knowledgeable learners, the performance is relatively high irrespective of the type of sorting, and the value of personalization is relatively low. Collectively, the arguments in favor of H1, H2, and H3 establish that the successful digital library and e-learning frameworks should combine system-level personalization with sensitivity to the heterogeneity of the learners.[11] Designers must thus establish adaptive ranking techniques that will support less skilled end-users, whilst still maintaining opportunities towards exploratory and critical search behavior to more expert learners.

Conclusion

This paper has looked into the effects of personalized algorithmic sorting on the performance of e-learners in Indian higher education in Information seeking and how the effects are influenced by prior knowledge of learners. With a quasi-experimental design and two-way ANOVA and moderation regression, the study goes beyond mere comparison of performance to indicate that the search results are jointly dependent on a system-level personalization and cognitive features. The findings indicate that individual sorting produces a significant positive effect on the composite Index of the Success of Information Seeking, whereas prior knowledge has a medium effect that is independent. Importantly, the effect of interaction in the model is significant, as well as the moderation coefficient (β= 0.29, $p < 0.05$), which allows confirming the idea that personalization is a compensatory effect, providing the greatest advantages to low-prior-knowledge learners. The results provide some new empirical data based on the Indian digital learning environment, where different language and education statuses of people render equal access to Information a burning issue. The research finds that properly designed adaptive ranking can result in reducing the gaps in performance by directing the low-experience learners to the relevant resources, but it does not significantly restrict high-prior-knowledge learners. The findings imply to the designers of digital libraries and e-learning environments that they must incorporate personalization strategies that are attuned to the heterogeneity of learners, which are transparent in their functions, and adaptable enough to facilitate the exploratory behavior. The proposed study ought to be extended by future studies by considering the long-term outcomes of this expansion on information literacy, analyzing the multilingual and culturally diverse context of using these algorithms, and understanding the impact of various types of algorithmic transparency and user control on trust and subsequent critical assessment and continued use of personalized information systems.

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