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Research Article
Improving Relevance of Information Retrieval Systems and User's Preferred Search Language

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Abstract

Background and Objective: Enhancing relevance of search results is becoming a crucial challenge for search engines. Collection of implicit and explicit feedback as indicators of search result relevancy is currently a growing interest in information systems research. While there is some evidence that individual differences affect the effectiveness of implicit indicators, little work investigated the potential effect of user's preferred search language in such context. The current study pioneered investigation of this effect on the relationship between a number of implicit indicators (dwell time, number of clicks and amount of scrolling) and user explicit rating. **Materials and Methods:** The experiment included 48 Arabic users divided in two groups, where only one group was given the option to select a preferred search language. The relationship between implicit indicators and explicit relevance ratings was examined using Pearson correlation. Significance testing was employed to ensure results from Pearson correlation are not random, where a confidence interval of 95% and a statistical significant coefficient, $p<0.05$, is accepted. To provide more confidence to the obtained results, t-value and standard deviation were calculated in the two groups. Significant differences between (number of clicks, amount of scrolling, dwell time) and relevance were ($t = 4.32$, $t = 5.11$, $t = 2.62$; $p<0.0005$) respectively. **Results:** Results suggested that the prediction level of implicit feedback for result relevance is enhanced when users are given the option to select a preferred language. The results also show that both the amount of scrolling and number of mouse clicks have higher precision with post-retrieval document relevancy compared to dwell time. Finally, the present study suggests that the prediction performance of dwell time varies from factual to intellectual task type. **Conclusion:** The current study provides a cost-effective method for understanding user behavior in the context of different languages through the use of implicit feedback. Findings of this study can be used to enhance the degree of result relevance for search-based recommender systems.

Key words: Preferred search language, implicit feedback, explicit feedback, search result relevance, information retrieval systems, dwell time, post-click behavior, information seeking behavior

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

With the enormous growth of information available over the internet and considering the current evolution of information searching and usage, finding relevant information is becoming a real challenge for online users. Improving user's online search experience is currently the main focus of information retrieval systems, namely web search engines. A growing body of research has been interested in enhancing the relevance of search results based on user's explicit and implicit feedback. While explicit feedback requires users to explicitly evaluate search result quality through answering questions, commenting and ranking, such feedback overloads users in terms of effort and time. Hence, considering users' implicit feedback is currently gaining interest since it can be gathered at no cost and in large quantities. Implicit feedback involves capturing user's search behaviors, such as dwell time (the amount of time spent on a search result page), clicking (number of mouse clicks on a page), scrolling (amount of scrolling done on a page), copying, printing and bookmarking. Such behaviors are captured usually via recording software while users perform specific task on computers.

Previous studies[1-5] have linked implicit feedback with user's explicit rating and suggested that implicit feedback can improve the relevance level of search results; nevertheless, these previous studies incorporated different approaches. Dwell time, one of the most extensively studied behaviors, was recently discovered to have modest accuracy[1]. While for some early studies, a single implicit indicator alone, such as dwell time, was found enough to indicate a document's usefulness[1-3], more recent studies have found that integration of many implicit and explicit approaches better indicates search result relevance compared with using a single implicit feedback[4,5]. These studies suggested that integrating post-click behaviors together (e.g., cursor movements, dwell time and scrolling on a clicked page) was significantly more effective than using page dwell time information alone for estimating the explicit judgments of each user.

Recent studies have indicated that a combination of implicit feedback may be related to search result usefulness more accurately when tailored to a specific user and moderated according to the task type[6-8]. These studies recommended that for an online information retrieval system to employ user search behaviors to infer search result preference, it is necessary to model the user's information-seeking context[9]. It was suggested that user search behavior differed according to user's characteristics[10,11], particular task[5], topic familiarity[12] and search context[13]. Previous study[6-8] linking user's implicit feedback and explicit relevance rating for a search engine results page rarely looked at the effect of user's differences. No previous study investigated the effect of user's preferred search language, which is the focus of the current work.

The current study investigates post-click user search behaviors (dwell time, amount of clicks and amount of scrolling) and relates them with explicit relevance rating, while looking at the effect of user's preferred speakers and whether user's preferred search language affects the relationship between implicit indicators (dwell time, number of clicks and amount of scrolling) and the explicit relevance rating for online search results. The experiment conducted herein involved two groups of online users, where only one group was given the option to select a preferred search language. Implicit feedback was collected via recording software while participants performed a self-predefined search task. Implicit data were compared with the explicit rating of search result relevance by users on a 5-point scale. The effect of preferred language on the relationship between implicit and explicit data was assessed for the two groups using correlation significance testing. The results of the current study have additional implications for better estimating document relevance for online search engines, namely in a non-English search context.

Implicit feedback is collected unobtrusively by observing user behavior while performing specific tasks. Dwell time, scrolling, saving, bookmarking and eye gaze are the most commonly collected parameters in implicit feedback research. With explicit feedback, users explicitly rate their interaction with a system through answering questions, commenting and ranking. Compared with explicit feedback, implicit data were reported to be less accurate[7]. However, it was reported that when users provide explicit feedback, it affects their normal reading and browsing pattern[14]. Lately, implicit feedback has been massively used to indicate user's behavior with information retrieval systems, especially since they have been shown to improve search result relevancy[4,6-8,15].

Early studies on user behavior support the notion that a single implicit feedback can play an important role in improving search relevancy. Previous study[16] investigated click frequency (number of mouse clicks on a page) feedback in an evaluation of 3000 queries of a search engine. Results revealed that click frequency alone can be a good indicator of relevant results. Another study[17] examined click-through logs and found that a large number of user clicks indicated relevance preference. Several studies looked at dwell time as a single indicator for results relevance. For example, the usefulness of dwell time as a measure of user interest in a document becomes more useful as the task becomes more complex[16]. Similarly, dwell time by itself can be a reliable indicator for document usefulness[17], especially in factual tasks. However, other research argued that high dwell time on a search result page does not necessarily parallel its relevance as a user may leave a page open for a long time without gazing at it[6]. In fact a user might spend a long time looking for relevant information on an apparently promising page but fail to find the needed information, such a document is obviously not relevant[8].

More recent studies suggested that using a single implicit feedback, such as click-through and dwell time, alone is insufficient to distinguish between relevant and non-relevant documents. These studies recommended integrating two or more implicit feedbacks. For example, integration between dwell time and copy amount is indicated to have a higher correlation with explicit ratings than a single indicator[6]. Similarly, it was found that dwell time alone is insufficient for differentiating between relevant and non-relevant documents and that text selection is more precise than dwell time[7]. They also suggested a method that integrates text selection, dwell time, click-through and page review to improve search result relevancy. Likewise, aggregation of dwell time with other feedback indicators, such as cursor movements and scrolling, can serve as a better indication of relevance and this aggregation was found to be significantly more effective than using dwell time alone for ranking search results[8].

Recent studies on user behavior have indicated that the prediction accuracy of implicit feedback improves when considering user personalization and task type[6-8]. Additionally, user search behavior has been shown to differ significantly according to preferences, characteristics, task and search context. It is therefore, necessary to model the user's individual characteristics and information-seeking context[9]. The user's preferred language versus the system's is suggested to generally affect user-system interaction[14,18]. More specifically, in a retrieval system, user-preferred language appears practical for granting ratings to documents written in this language[19]. Recently, search engines have started to pay attention to user language identification. Widely used search engines, such as Google, are taking note of user-preferred language as well as ranking of search results by language, to improve search result relevance. Recognizing user-preferred language is usually done via query term language and/or search interface. User-preferred language identification via query term has been introduced in a patent for Google[19]. Nonetheless, no other previous study has investigated the effect of user's preferred language on implicit feedback as an indicator of result relevance, which is the focus of the present study.

The current study aimed to investigate the effect of user's preferred search language on the extent with which implicit indicators match the explicit relevance rating of online search results. The results of the present study can contribute to a better understanding of online search result relevance, namely in a non-English search context.

MATERIALS AND METHODS

Implicit data was captured unobtrusively as users browsed a search engine, while explicit data were collected using a 5-point scale rating. Description of implicit indicators and explicit ratings are shown in Table 1.

Sample: Forty-eight master's degree students from different educational emphases (computer science, finance, management and accounting) working as teaching assistants at a university in Egypt participated in the experiment. Recruitment was conducted through open calls via emails. Participants volunteered to take part in the experiment with no monetary compensation; a certificate of appreciation and a thank you letter was given after completion of the experiment. Participant ages ranged between 22 and 39 years and 69% were females. Participant's proficiency with the English language and online search skills (both self-reported in a summary questionnaire administered at the end of sessions) were intermediate to high. All participants were native Arabic speakers, teaching and conducting research in English.

Experimental design: Participants were randomly divided into two groups of 24 each. The search engine assigned to one group Google.com, ensuring the search results would be in English only (NoPrefLang group). The other group's search engine was Google.com.eg, wherein participants had the

Table 1: implicit indicators and explicit relevance rating

Parameters	Description[6]
Dwell time	The accumulated time in seconds spent by a user on an active page
No. of mouse clicks	The incremented count any time a mouse clicks on a page
Amount of scrolling	The incremented count any time a user clicks the scrollbar up or down
Explicit relevance ratings	The actual rating of the page by the user on a five-point scale, 5: Very relevant, 1: Not relevant

option to select their preferred search language, Arabic or English (PrefLang group). Experimental sessions were conducted in November and December, 2016 in a university computer lab. Participants worked on a desktop computer with high-speed internet connectivity. The search engine used was Google Chrome and Morae Recorder was used to record dwell time, number of clicks and amount of scrolling for each search result page. Explicit data were collected using a 5-point relevance rating scale (5 = Very relevant, 1 = Not relevant). This scale was validated in a previous study having similar context as the current study[15].

An orientation was held with participants a week before the experiment to explain that the objective was to explore the general use of search engines but no details concerning the study hypotheses were given. Participants were asked to identify a range of search tasks they would need to perform within the week. The search task defined for the current study was the goal of information-seeking behavior. Participants were asked to write down their information-seeking needs during the week but not conduct an online search of these tasks; instead, they were to come to each session with this list of tasks. Participants were informed that all activities performed on the computer would be recorded using special software during each experimental session. The email of the researcher was given to participants to send queries about details of the study and to request a copy of the final results.

A questionnaire that collected demographic data as well as English language and search skill proficiency level, was administered by the researcher through a semi-structured interview for 10 min directly after each session. This allowed exploration of further search behaviors and preferences expressed by participants. Overall, the experiment included forty-eight sessions, each session lasted around 60 min for each participant. Feedback from the exit interview confirmed that participants were able to perform the experiment consistently and with minor problems.

Task description: To study a variety of search tasks within a short span of time, a list of predefined search tasks, participants previously identified before the experiment, based on their information seeking needs a week before the experiment, was used. Participants were informed that these tasks must be independent of each other and could be work-related, academic-related and/or personal. This method of task identification was preferred to motivate participants as these tasks are based on participant's real needs. Tasks identified by participants are displayed in Appendix 1 for research reasons, they were categorized by the researcher as factual and intellectual tasks. Factual tasks are concerned with gathering specific information explicitly measured, while intellectual tasks involve searching an approach for making a decision to solve a complex problem[5]. Search tasks were of different categories, such as "Checking weather", "Checking conference dates and venues", "Preparing course materials", "Literature review for dissertation" and "Applying for research grants".

No time limit was given to execute each search task to remove any anxiety; however, participants were required to perform at least five search tasks from their predefined list. Participants were instructed to save pages they opened with a file name equal to the relevance rating they gave for that page. For example, if the page was rated "Very relevant", it should be saved with a "5" as the file name. Relevance was defined for participants as how appropriate (related) participants believed pages were in helping them to complete and/or understand the particular search task. For each search task, participants were required to do the following:

- Enter their own query in the search engine and select a preferred search language (only one group)
- Select and read search result page(s), save the page on the computer hard disc with a file name reflecting their relevance rating, then close the current tab (the search result page)

During the search, all participants' interactions with the computer were logged via the Morae Recorder, a screen capture program which recorded and remotely observed user interactions on computers; Morae Recorder software was run simultaneously with the search engine. The number of clicks and number of clicks on scroll bar (amount of scrolling) were counted. Dwell time for each search result link was automatically calculated by subtracting the difference in start time: T1 was the time when the user performed an action, such as entering a query and clicking search or returning to search results page, T2 was the time when users displayed one of the search results by following one of the links (e.g., Link1) and T3 was the time when users left Link1. Dwell time was the difference between T1 to T2 and from T2 to T3. For identical links viewed at different times (e.g., if the user went back to Link1), T2 times were added to arrive at the total dwell time for each link. Matching implicit feedback of a page with its relevance rating was performed manually.

Statistical analysis: An experiment was conducted involving two groups of online searchers, where only one group was given the option to select preferred search language. Implicit feedbacks were collected via a recording software, while participants performing a self-pre-defined search task. Implicit data were compared with the explicit rating of search result relevance, completed by the users via a five point scale. The effect of preferred language on the relationship between implicit and explicit data was assessed for the two groups using correlation significance testing.

Significance testing was employed to ensure if results from Pearson correlation are not random, where a confidence interval of 95% and a statistical significant coefficient, $p<0.05$, is accepted[6]. Null hypothesis indicates that there is no statistical significant relationship or association between two measured parameters. When the null hypothesis is rejected, it means there is evidence that there is a relationship between two parameters. When significant coefficient $p = 0.05$, the null hypothesis is accepted and there is no significant relationship is considered, a significant coefficient $p<0.05$ indicates that null hypothesis is rejected and a significant relationship is suggested. To provide more confidence to the obtained results, t-value and standard deviation were calculated to check if there was a significant difference ($p<0.05$) between implicit indicators and the explicit relevance rating in the two groups[6].

RESULTS AND DISCUSSION

The overall data collected in this study is displayed in Table 2. For each group, every participant in each group visited at least one search result link while performing each search task. The maximum number of links visited by a participant in a single task was 3; a total of 246 web pages were analyzed for all participants in both groups.

Implicit indicators and explicit relevance: The relationship between implicit indicators (dwell time, number of clicks and amount of scrolling) and explicit relevance ratings (5-point scale) was examined using Pearson correlation. Based on results listed in Table 3, a positive correlation was observed between explicit relevance rating and implicit indicators only in the PrefLang. This relationship was not significant in the NoPrefLang group. The correlation coefficient between implicit indicators and explicit relevance ratings obtained in the

Table 2: Collected data

NoPrefLang				PrefLang			
Par#	Task#	Link#	Relv (S.D.)*	Par#	Task#	Link#	Relv (S.D.)*
1	5	5	4.77 (1.54)	1	5	6	5.52 (1.81)
2	7	12	5.88 (1.99)	2	8	19	6.15 (2.31)
3	9	15	5.43 (2.19)	3	5	5	4.77 (1.54)
4	6	18	5.95 (1.90)	4	7	12	5.88 (1.99)
5	5	11	4.51 (1.80)	5	5	15	5.78 (1.55)
6	8	16	5.14 (2.30)	6	9	9	6.89 (2.00)
7	5	15	3.76 (1.53)	7	6	8	6.44 (2.20)
8	7	9	4.87 (1.98)	8	6	12	6.96 (1.20)
9	6	10	4.42 (2.18)	9	9	19	5.52 (1.81)
10	7	15	4.94 (1.92)	10	6	15	6.16 (2.31)
11	6	6	4.68 (1.44)	11	7	12	4.52 (2.81)
12	5	18	4.78 (1.71)	12	9	18	5.15 (2.51)
13	7	15	5.52 (2.29)	13	5	13	4.57 (1.34)
14	5	17	5.96 (1.93)	14	7	12	5.78 (1.79)
15	5	10	4.32 (1.75)	15	5	14	5.58 (1.75)
16	7	13	5.24 (2.43)	16	8	8	6.79 (2.32)
17	6	12	3.56 (1.13)	17	6	8	6.54 (2.50)
18	5	9	4.67 (1.78)	18	6	9	6.76 (1.29)
19	6	11	4.72 (2.48)	19	7	19	5.72 (1.71)
20	7	14	4.74 (1.72)	20	5	15	6.76 (2.51)
21	7	11	4.67 (1.68)	21	7	12	4.57 (2.86)
22	5	10	4.32 (2.38)	22	8	11	5.18 (2.54)
23	8	15	4.74 (1.72)	23	6	12	4.67 (1.44)
24	6	11	4.48 (1.24)	24	6	12	4.78 (2.69)

PrefLang: Group given the option to select a preferred search language (Arabic or English), NoPrefLang: Group not given a language option (English only), #Par: No. of search tasks, #Task: No. of search result links viewed, #Link: No. of links, *Relv, the mean and (SD: Standard deviation) of links rated as relevant, data presented under #Par, #Task and #Link represent the number of participants

Table 3: Pearson correlations between implicit indicators and explicit relevance rating

	NoPrefLang		PrefLang	
Implicit Indicators	Pearson correlation (r) with explicit rating	Significance coefficient (p)	Pearson correlation (r) with explicit rating	Significance coefficient (p)
Dwell time	-0.71	0.470	0.395	0.000
No. of clicks	-0.16	0.642	0.291	0.000
Amount of scrolling	-0.68	0.541	0.389	0.000

PrefLang: Group given the option to select a preferred search language (Arabic or English), NoPrefLang: Group not given a language option (English only)

Table 4: t-value of significant differences between implicit indicators and explicit relevance rating

	NoPrefLang	PrefLang
Dwell time	Average time (sec)	Average time (sec)
Mean dwell time of relevant search results	29.37	50.19
Mean dwell time of non-relevant search results	29.22	33.10
Calculated t-value	1.89	2.750
No. of clicks	Average No.	Average No.
Mean no. of clicks of relevant search results	3.71	4.17
Mean no. of clicks of non-relevant search results	2.21	1.91
Calculated t-value	1.32	4.41
Amount of scroll	Average No.	Average No.
Mean amount of scrolling of relevant search results	1.07	3.54
Mean amount of scrolling of non-relevant search results	0.66	0.86
Calculated t-value	1.45	5.16

PrefLang: Group given the option to select a preferred search language (Arabic or English), NoPrefLang: Group not given a language option (English only), Bolded number means significant difference found between relevant and non-relevant links (p<0.0005)

current study is higher than those obtained in previous studies[8,6] conducted under a similar context.

To provide more confidence for the obtained results, t-values and standard deviation were calculated to check if there was a significant difference ($p<0.05$) between implicit indicators and the explicit relevance rating in the two groups. As indicated in Table 4, a significant difference was found between dwell time for relevant and non-relevant links ($t = 2.75$, $p<0.0005$) only in the PrefLang group. This suggests that the relationship between time spent reading search results and result relevance is significant when users are given the option to select a preferred search language. Similarly, a significant level was found between number of clicks for relevant and non-relevant links ($t = 4.41$, $p<0.0005$) only in the PrefLang group. This suggests that the relationship between amount of clicks while reading search results and result relevance is significant when users are given the option to select a preferred search language. Finally, a significant level was found between amount of scrolling for relevant and non-relevant links ($t = 5.16$, $p<0.0005$) only in the PrefLang group. This suggests that the relationship between amount of scrolling while reading search results and result relevance is significant when users are given the option to select a preferred search language. It is worth mentioning that the significant level in the relationship between number of clicks and relevance as well as amount of scrolling and relevance, are considerably higher ($t = 4.41$ and $t = 5.16$, respectively; $p<0.0005$) than that between dwell time and relevance ($t = 2.75$, $p<0.0005$). This suggests that the implicit indicators number of clicks and amount of scrolling better predict search result relevance compared to dwell time when users are given the option to select a preferred search language.

Dwell time for different task types: Follow-up tests were conducted to investigate the relationship between dwell time and relevance for different task types (factual versus intellectual search tasks). Results suggested that short dwell times are associated with irrelevant results only in the case of factual search tasks. As for intellectual search tasks, a correlation between dwell time and relevance could not be detected. This might be justified as participants would spend longer time on intellectual documents before deciding its relevance. This result agrees with some previous research suggesting that the prediction performance of implicit indicators varies from factual to intellectual task type[2,4,5,20]. While it seems logical that intellectual documents usually require more time to read in order to judge their relevance compared with factual documents, more investigation is needed to determine a task-based relationship between implicit indicators and relevance within a preferred language context.

CONCLUSION, IMPLICATIONS, LIMITATIONS AND FUTURE WORK

The current study confirmed the predictive strength of implicit feedback (dwell time, number of clicks and amount of scrolling) for information relevance. The study verified these implicit feedback as indicators of search result relevancy, while considering user's preferred search language. Results showed that implicit indicators could predict search results relevance when users are given the option to select a preferred search language. Furthermore, short dwell times was found to be indicative to search result irrelevance, namely in factual search tasks. Such findings can have practical implications for enhancing relevance of post-retrieval documents in search engines. Results from this study can be employed to assist non-English speaker's users to retrieve relevant web documents in an interactive information retrieval bi-language environment.

At the methodological level, the main significance of the current study is its consideration of the language preference factor in a non-native English language search context. The results suggest that specific implicit constructs have a significant correlation ($p<0.05$) with explicit relevance when the user's preferred language is considered. These results confirm implicit feedback models suggested in other studies and also validates these models in a non-English search context. The current results also suggest that using various user feedback within the same context, such as number of clicks and amount of scrolling, provides advantages over using dwell time alone, confirming the prediction strength of these implicit constructs over dwell time; similar results were also suggested in other studies. Furthermore, the amount of scrolling was also found to have the highest precision, followed by number of mouse clicks, compared to dwell time and number of mouse clicks.

Practically speaking, these findings demonstrate a cost-effective method for understanding user behavior in a language differences context through the use of implicit feedback. These findings contribute to the practical implications of current results for search engine design and development. In agreement with other recent studies[6-9], present results suggest it is important for these systems to provide personalized search results. Moreover, the present study highlights the effect of user's preferred language or languages and the need for search engines to learn more about this factor so as to achieve optimal prediction performance.

The present results are restricted to the experimental environment used herein. In real-world scenarios, dwell time may also include time periods during which the user is not looking at the computer screen. To ensure that dwell time is only measured when the user is looking at the page onscreen, use of a web cam might be a good idea when capturing implicit feedback. Additionally, participants were a convenient sample with intermediate to advanced search skills and English language proficiency. This may not reflect the behavior of average non-native English speaking users. Thus, preferred language might have a higher effect on search result relevance for users different with demographic characteristics. Furthermore, the effect of search task type (factual versus intellectual) on result relevance was not explored in depth in the current study. Future work based on the current research should integrate the effect of task type with preferred language for better prediction of result relevance in non-English language search contexts. Future study should also further explore implicit feedback indicating relevance, such as page review and text selection, in a language preference context.

SIGNIFICANCE STATEMENTS

This study verifies the possible power of dwell time, number of clicks and amount of scrolling in the prediction of search results relevance; this power is strengthened when users are given the option to select a preferred search language. This study introduces the search language preference as a novel construct. The study also suggests a method for understanding user behavior in the context of multi-languages search-based recommender systems through the use of implicit feedback. The results of the present study can contribute to a improve search result relevance for search-based systems.

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Appendix 1: Search tasks preselected by participants

Factual tasks	Check Weather; Check Transportation Schedule; Booking Quotes; Shopping Item Prices; Translation; Checking News Bar; Movie Schedules; Hotel Review; Payment Online; Checking Bank Balance; Looking up for Address; Finding Book in E-Library; Checking Academic Calendar on University Home Page; Checking Conference Date and Venue
Intellectual tasks	Reading Research Article; Prepare Course Materials; Literature Review for Dissertation; Taking a Course on MOOCs; Looking for Scholarships Opportunities; Applying for Research Grants; Learning Statistical Technique; Online Debugging for Software Codes; Filling an Academic Staff Survey; Reviewing a Journal Article; Updating Staff Record; Compiling Lecture Power Points; Selecting Case Studies for a Course

REFERENCES

1. Kelly, D., 2004. Understanding implicit feedback and document preference: A naturalistic user study. ACM SIGIR Forum, 38: 77-77.
2. Kellar, M., C. Watters, J. Duffy and M. Shepherd, 2004. Effect of task on time spent reading as an implicit measure of interest. Proc. Am. Soc. Inform. Sci. Technol., 41: 168-175.
3. Kelly, D. and N.J. Belkin, 2004. Display time as implicit feedback: Understanding task effects. Proceedings of the 27th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, July 25-29, 2004, Sheffield, UK., pp: 377-384.
4. Buscher, G., R.W. White, S. Dumais and J. Huang, 2012. Large-scale analysis of individual and task differences in search result page examination strategies. Proceedings of the 15th ACM International Conference on Web Search and Data Mining, February 8-12, 2012, Seattle, Washington, USA., pp: 373-382.
5. Liu, Y., J. Miao, M. Zhang, S. Ma and L. Ru, 2011. How do users describe their information need: Query recommendation based on snippet click model. Expert Syst. Applic., 38: 13847-13856.
6. Akuma, S., C. Jayne, R. Iqbal and F. Doctor, 2014. Implicit Predictive Indicators: Mouse Activity and Dwell Time. In: Artificial Intelligence Applications and Innovations, Iliadis, L., I. Maglogiannis, H. Papadopoulos, S. Sioutas and C. Makris (Eds.). Springer, New York, pp: 162-171.
7. Balakrishnan, V. and X. Zhang, 2014. Implicit user behaviours to improve post-retrieval document relevancy. Comput. Hum. Behav., 33: 104-112.
8. Guo, Q. and E. Agichtein, 2012. Beyond dwell time: Estimating document relevance from cursor movements and other post-click searcher behavior. Proceedings of the 21st International Conference on World Wide Web, April 16-20, 2012, Lyon, France, pp: 569-578.
9. Gonzalez Ibanez, R. and C. Shah, 2016. Using affective signals as implicit indicators of information relevance and information processing strategies. Proc. Assoc. Inform. Sci. Technol., 53: 1-10.
10. Kelly, D. and J. Teevan, 2003. Implicit feedback for inferring user preference: A bibliography. ACM SIGIR Forum, 37: 18-28.
11. Lin, S.J. and N.J. Belkin, 2000. Modeling multiple information seeking episodes. Proceedings of the 63th Annual Meeting of the Association for Information Science and Technology, November 13-16, 2000, Chicago, IL., USA., pp: 133-146.
12. Kelly, D. and N.J. Belkin, 2000. Modeling characteristics of the user's problematic situation with information search and use behaviors. Proceedings of the 2nd ACM/IEEE Joint Conference on Digital Libraries, July 13-17, 2002, Portland, Oregon.
13. Loch, K.D., D.W. Straub and S. Kamel, 2003. Diffusing the Internet in the Arab world: The role of social norms and technological culturation. IEEE Trans. Eng. Manage., 50: 45-63.
14. Claypool, M., P. Le, M. Wased and D. Brown, 2001. Implicit interest indicators. Proceedings of the 6th International Conference on Intelligent user Interfaces, January 14-17, 2001, Santa Fe, New Mexico, USA., pp: 33-40.
15. Akuma, S., R. Iqbal, C. Jayne and F. Doctor, 2016. Comparative analysis of relevance feedback methods based on two user studies. Comput. Hum. Behav., 60: 138-146.
16. Agichtein, E., E. Brill and S. Dumais, 2006. Improving web search ranking by incorporating user behaviour information. Proceedings of the 29th Annual International ACM Conference on Research and Development on Information Retrieval, August 6-11, 2006, Seattle, Washington, USA., pp: 19-26.
17. Dou, Z., R. Song, X. Yuan and J.R. Wen, 2008. Are click-through data adequate for learning web search rankings? Proceedings of the 17th ACM Conference on Information and Knowledge Management, October 26-30, 2008, Napa Valley, California, USA., pp: 73-82.
18. El Said, G., 2013. Young Egyptians Use of Social Networks and the January 2011 Revolution. In: Design, User Experience and Usability: Health, Learning, Playing, Cultural and Cross-Cultural User Experience, Marcus, A. (Ed.). Springer, New York, pp: 38-43.
19. Lamping, J., B. Gomes, M. McGrath and A. Singhal, 2003. System and method for providing preferred language ordering of search results. Patent No. US 7,451,129.
20. White, R.W. and D. Kelly, 2006. A study on the effects of personalization and task information on implicit feedback performance. Proceedings of the 15th ACM International Conference on Information and Knowledge Management, November 5-11, 2006, Arlington, VA, USA., pp: 297-306.