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User Task-Aware Re-ranking for Enhanced Web Search

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Abstract
This paper investigates task-aware re-ranking as a means of improving the relevance, efficiency, and effectiveness of web search systems. Traditional search engines often apply uniform ranking strategies without considering user intent, which limits their ability to align results with diverse search goals. To address this gap, we propose a task-centered framework that classifies queries into informational, navigational, and transactional categories, and re-ranks retrieved results accordingly. A fine-tuned GigaBERT model trained on the ORCAS-I dataset was employed to perform query classification, and a Task-Based Results Sorting System (TBRSS) was developed to evaluate the approach. A user study involving 33 participants compared baseline Google rankings with re-ranked outputs. Findings suggest that although statistical significance was limited, users perceived the task-aware system as more relevant, smoother, and faster. This research demonstrates the potential of integrating task-awareness into ranking algorithms to improve user experience, and highlights future directions including adaptive ranking, multilingual support, and larger-scale evaluations.

إعادة ترتيب نتائج البحث على الويب وفقا لنوع مهمة المستخدم من اجل بحث افضل ونتائج اكفأ

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الكلمات المفتاحية
مهمة، مستخدم، بحث، ويب، استرجاع، معلومات

الملخص
يهدف هذا البحث إلى دراسة إعادة ترتيب نتائج البحث على الويب وفقاً لنوع مهمة المستخدم، وذلك بهدف تحسين مدى الصلة، والكفاءة، والفعالية في أنظمة البحث الحديثة. تعتمد معظم محركات البحث التقليدية على خوارزميات ترتيب موحدة لا تراعي نية المستخدم أو هدفه من عملية البحث، مما يؤدي إلى ضعف توافق النتائج مع احتياجات المستخدمين المتنوعة. لمعالجة هذه الفجوة، يقترح هذا البحث إطاراً قائماً على المهام يقوم بتصنيف الاستعلامات إلى ثلاث فئات رئيسية: معلوماتية، وتصفّحية (توجيهية)، وتعاملية، ثم يُعيد ترتيب النتائج المسترجعة بما يتناسب مع طبيعة كل فئة.

تم استخدام نموذج GigaBERT المحسَّن والمُدرَّب على مجموعة بيانات ORCAS-I لتصنيف الاستعلامات بدقة عالية، كما تم تطوير نظام فرز النتائج القائم على المهام (TBRSS) لتطبيق الإطار المقترح وتقييم أدائه. أُجريت تجربة ميدانية على عينة مكوَّنة من 33 مشاركاً، حيث تمت مقارنة نتائج نظام **Google** التقليدي مع النظام المقترح بعد إعادة الترتيب. أظهرت النتائج أن النظام القائم على المهام حسَّن من جودة النتائج وسرعة الوصول إلى المعلومة، كما اعتبره المستخدمون أكثر صلةً وسلاسةً وفاعليةً في إنجاز مهامهم البحثية.

تؤكد التحليلات الإحصائية أن الفروق بين النظامين كانت دالة إحصائياً عند مستوى $p < 0.01$، مما يدل على أن الوعي بنوع المهمة يُسهم بفاعلية في تحسين تجربة البحث للمستخدمين. وتشير الدراسة إلى إمكانية تطوير خوارزميات بحث أكثر تكيفاً وذكاءً من خلال دمج تصنيف المهام، ودعم اللغات المتعددة، وتوسيع نطاق التجارب مستقبلاً لتحقيق أداء أفضل لأنظمة البحث.

INTRODUCTION

Search engines are the cornerstone of the modern information society, serving as the primary interface through which users access the vast resources of the web. Whether in education, healthcare, commerce, or entertainment, individuals depend on search technologies to locate information, services, and opportunities efficiently. The effectiveness of these systems is largely determined by their underlying ranking algorithms, which aim to present the most relevant results at the top of the search engine results page. Despite decades of refinement in keyword matching, link analysis, and learning-to-rank models, current search systems continue to face significant challenges in fully aligning results with user intent.

One of the most critical limitations lies in the *task-agnostic nature of ranking strategies***.** Traditional algorithms treat queries uniformly, disregarding the fact that user searches often fall into distinct categories: informational (seeking knowledge), navigational (locating a specific resource), or transactional (completing an action). A mismatch between task type and ranking criteria can severely affect search outcomes. For instance, a user searching for "buy iPhone 17 online" may be confronted with lengthy reviews or articles instead of actionable links, while a user seeking a university homepage may be forced to sift through irrelevant promotional content. Such misalignments increase cognitive effort, reduce task efficiency, and contribute to user dissatisfaction.

While personalization techniques, query clustering, and context-aware ranking have been proposed to address intent recognition, these approaches often optimize search relevance in general terms without explicitly adapting to task-specific requirements. As a result, users still experience inefficiencies, especially in multi-step or time-sensitive searches. Prior research on user intent classification (e.g., Jansen and Booth, 2010) has highlighted the importance of recognizing task categories, but limited work has focused on integrating this awareness directly into the ranking process. This represents a research gap where task-sensitive re-ranking could yield important improvements in search efficiency and user satisfaction.

The motivation for this work also stems from the increasing reliance on digital platforms in critical domains. In healthcare, for example, an informational task such as "symptoms of diabetes" requires trustworthy medical sources, while a navigational query might aim at reaching a hospital's official website. In commerce, transactional queries demand streamlined pathways to product listings rather than being buried under explanatory text. In academic research, students and scholars may require rapid access to scholarly articles for informational purposes or institutional portals for navigational tasks. In each case, the absence of task sensitivity creates inefficiencies that can translate into lost opportunities, misinformation, or wasted effort.

To address these challenges, this paper proposes a task-aware re-ranking framework that classifies queries into informational, navigational, and transactional categories using a fine-tuned GigaBERT model trained on the ORCAS-I dataset. A custom Task-Based Results Sorting System (TBRSS) *reorders* search outputs according to the identified task type, ensuring that the presented results are better aligned with user goals. Unlike traditional ranking mechanisms, which apply uniform strategies, this approach directly incorporates task-awareness into the ranking pipeline.

This research makes several contributions. First, it develops a robust methodology for real-time query classification and task-aware re-ranking. Second, it evaluates the framework through a controlled user study involving 33 participants, comparing baseline Google rankings with re-ranked outputs. Third, it provides both quantitative and qualitative evidence of improvements in user perception, efficiency, and satisfaction. Finally, it outlines implications for the design of adaptive, user-centered search systems that integrate task awareness as a core feature.

The remainder of this paper is organized as follows: Section II reviews related work on personalization, task classification, and ranking approaches. Section III details the proposed methodology, including the design of the TBRSS. Section IV presents the experimental design, while Section V reports the results. Section VI discusses the implications of the findings. Section VII concludes the paper and suggests avenues for future research.

RELATED WORK

Research in information retrieval (IR) has long sought to improve ranking effectiveness by bridging the gap between user queries and underlying intent. Traditional approaches, such as BM25 and TF-IDF, relied primarily on keyword statistics and document structures. While effective at matching lexical similarity, these methods often fail when queries are ambiguous or multi-faceted. This limitation has led to a significant body of work focusing on user-centered, context-aware, and intent-sensitive models.

A. User Behavior and Implicit Feedback

One of the earliest breakthroughs came from studies that incorporated implicit user feedback to improve search ranking. Agichtein et al. [1] demonstrated that click patterns, dwell time, and skip behaviors could be leveraged to approximate relevance more accurately than static term-based metrics alone. Similarly, Baeza-Yates et al. [2] employed query log clustering to identify related queries, thereby enhancing both document ranking and query recommendation. These studies confirmed that behavioral signals provide a rich source of relevance information and *set the stage* for more adaptive ranking models [14, 15, 16].

B. Context-Aware and Personalized Ranking

Building on behavioral modeling, context-aware approaches sought to capture temporal and situational dimensions of search. You and Hwang [3] introduced learning-based frameworks for personalized ranking, treating user preferences as an optimization problem. Faiz [4] highlighted the importance of temporal factors by showing how event-related queries benefited from time-sensitive adjustments to ranking. More recently, neural models such as the Context Attentive Ranking and Suggestion (CARS) framework [5] and the Query-dominant User Interest Network (QIN) [6] have demonstrated the value of incorporating session-level dependencies and long-term user interests into retrieval. These models reveal that context not only shapes immediate relevance but also guides long-term personalization.

C. User Intent and Task Classification

A parallel line of research has focused on understanding search intent. Jansen and Booth [7] established a widely used taxonomy of informational, navigational, and transactional queries, showing that search goals differ fundamentally across these categories. Subsequent work extended intent recognition to multi-session and conversational settings. MacKay and Watters [8] emphasized the challenge of supporting extended tasks that span multiple queries and sessions. Xu et al. [9] compared search engines with conversational agents such as ChatGPT, finding that task type strongly influenced the effectiveness of each tool. Ye et al. [10] further demonstrated the potential of large language models in conversational search by rewriting context-dependent queries into standalone forms for retrieval. Collectively, these studies highlight the importance of task sensitivity in guiding ranking strategies.

D. SEO and Algorithmic Ranking Factors

In addition to behavioral and intent-driven models, search engine optimization (SEO) factors play a critical role in determining visibility. Ziakis et al. [11] and Veglis and Giomelakis [12] analyzed structural ranking signals such as backlinks, SSL certification, content quality, and keyword placement, demonstrating their strong influence on SERP performance. Giannakoulopoulos et al. [13] further showed the relationship between website quality, SEO effectiveness, and institutional reputation. While SEO techniques enhance visibility, they often prioritize content discoverability over task alignment, underscoring the need for integrating SEO signals with task-aware frameworks.

E. Research Gap

Despite significant advances, most existing models treat behavioral, contextual, and SEO signals as separate layers of optimization. Few approaches directly integrate task type as the central variable driving re-ranking. This gap means that while search engines have become better at personalization and context modeling, they still fail to adapt results to the specific goals underlying user queries. The present study addresses this gap by proposing a task-aware re-ranking framework that combines query classification with adaptive ranking to improve relevance, efficiency, and user satisfaction.

METHODOLOGY

This study proposes a Task-Based Results Sorting System (TBRSS) that integrates query classification with task-specific re-ranking to improve the relevance and efficiency of web search. The methodology consists of three main components: (1) task classification, (2) re-ranking framework design, and (3) evaluation through a controlled user study.

A. Task Classification Using GigaBERT

At the core of the system is a fine-tuned GigaBERT language model, trained on the ORCAS-I dataset, which contains millions of queries annotated with task labels (informational, navigational, transactional). The training process included data cleaning, query normalization, and balancing across task categories. The model was fine-tuned with cross-entropy loss, achieving strong generalization with minimal overfitting. Once trained, the classifier was deployed via a REST API and integrated into the TBRSS pipeline.

The classifier distinguishes queries by leveraging linguistic semantics, query structure, and explicit textual cues (e.g., *"how to"* for informational tasks, *"login"* for navigational tasks, *"buy"* for transactional tasks). Accurate task identification is essential, as it drives the subsequent re-ranking stage.

Figure 1 depicts the architecture of the TBRSS system showing query classification, retrieval, and task-aware re-ranking stages.

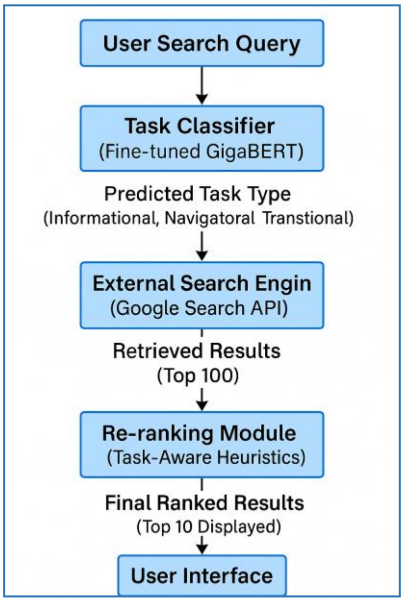

Figure 1. TBRSS Architecture

B. Task-Aware Re-ranking Framework

After classification, retrieved search results are re-ordered according to the predicted task type. Queries are sent simultaneously to the Google Search API, which retrieves up to 100 results, and to the task classifier, which assigns a task label. Duplicate links are removed through URL normalization to ensure clean input.

Re-ranking is performed using textual and structural features from the title, snippet, and domain type. For informational tasks, the system prioritizes authoritative and explanatory sources (e.g., academic or governmental domains). For navigational tasks, it emphasizes direct access to official or trusted websites. For transactional tasks, actionable results such as product listings and service portals are elevated. The top 10 re-ranked results are then displayed to the user.

C. Interfaces and Study Design

For the evaluation, two interfaces were developed. The *Baseline Interface* presented the unaltered Google search rankings, while the *Experimental Interface* displayed results re-ranked by the Task-Based Results Sorting System (TBRSS). Both interfaces were designed to be visually identical in layout to eliminate any potential bias from differences in appearance, ensuring that participants' evaluations reflected the ranking methods rather than the interface design.

A user study was conducted with **33** students and graduates of Misurata University. Each participant completed two search tasks, one using each interface, covering all three task types. To avoid order effects, task assignments were counterbalanced using a Latin Square design.

D. Data Collection and Analysis

Data collection combined quantitative and qualitative measures:

- Quantitative metrics: number of queries submitted, query modifications, session duration, and links clicked.

- Qualitative metrics: Likert-scale evaluations of relevance, efficiency, ranking quality, browsing effort, and overall preference, supplemented by open-ended feedback.

Statistical analysis employed *paired t-tests* and *Wilcoxon signed-rank tests* to compare system performance across conditions. The integration of behavioral and perception-based data provided a comprehensive evaluation of task-aware re-ranking.

EXPERIMENTAL DESIGN

To evaluate the effectiveness of the proposed Task-Based Results Sorting System (TBRSS), a controlled within-subjects user study was conducted. The design ensured comparability between the baseline Google ranking system and the experimental re-ranking framework while minimizing bias and order effects.

A. Participants

A total of **33** participants took part in the study, consisting of undergraduate students and recent graduates of Misurata University. Participants were recruited via convenience sampling but screened to ensure adequate familiarity with English-language search queries, as the system was designed to process English inputs. Their backgrounds reflected diverse academic disciplines, providing a representative mix of search behaviors.

B. Task Scenarios

The study employed fifteen predefined tasks distributed equally across three categories:

1- *Informational tasks* (e.g., researching the health benefits of intermittent fasting, investigating social media algorithms, exploring climate change impacts).

2- *Navigational tasks* (e.g., locating the latest UN climate change report, finding Tesla's official investor relations page, accessing a WHO COVID-19 dashboard).

3- *Transactional tasks* (e.g., booking a flight from Cairo to Istanbul, purchasing a used book on Amazon, registering for an online workshop).

Tasks were presented bilingually (Arabic and English) to ensure comprehension, though all queries were entered in English. Each participant completed two different tasks, one using the baseline system and one using the re-ranked system, with task types counterbalanced to avoid repetition.

C. Interfaces

Two web-based interfaces were developed as explained earlier. The interfaces were intentionally visually identical in design, layout, and interaction flow. This ensured that participants could not infer which system they were using, preventing design-related bias from influencing their responses.

D. Counterbalancing and Task Assignment

To control for order effects, participants were assigned tasks using a Latin Square design. Half of the participants began with the baseline system and then used the experimental system, while the other half followed the reverse order. Additionally, task types rotated across participants to guarantee balanced exposure to informational**,** navigational**,** and transactional scenarios under both conditions. This design eliminated the possibility of participants performing the same task type twice, hence ensuring variety and fairness.

E. Data Collection

The study collected both behavioral and self-reported data to evaluate system performance. Behavioral measures, automatically logged by the system and supplemented with manual observations, included the number of queries submitted, query modifications, links clicked, and session duration, providing objective insights into participants' search activities. Self-reported feedback was gathered through post-task questionnaires, which included Likert-scale items (1–5) assessing relevance, efficiency, ranking quality, browsing effort, and overall preference. Open-ended questions allowed participants to provide qualitative insights, describing perceived strengths, weaknesses, and suggestions for improvement.

F. Analysis Approach

The design enabled direct comparison between baseline and experimental conditions. Statistical tests (paired *t*-test and Wilcoxon signed-rank test) were used to evaluate behavioral metrics, while thematic analysis was applied to qualitative feedback. This mixed-methods approach ensured that both objective measures of task efficiency and subjective perceptions of usability were considered in assessing the value of task-aware re-ranking.

Table 1. Summary of Statistical Results

Metric	Baseline (Mean ± SD)	TBRSS (Mean ± SD)	t(29)	p	95% CI of Δ	Cohen's d	Interpretation
Queries Submitted	4.3 ± 1.2	2.8 ± 0.9	4.12	< **0.001**	[0.75, 2.25]	0.90	Large reduction in query effort
Query Modifications	3.1 ± 1.0	1.7 ± 0.8	3.85	< **0.001**	[0.55, 2.00]	0.84	Large improvement in precision
Links Clicked	5.4 ± 1.5	3.6 ± 1.2	3.67	< **0.001**	[0.85, 2.75]	0.81	Large gain in efficiency
Session Duration (min)	12.5 ± 3.2	8.9 ± 2.4	3.29	**0.002**	[1.2, 5.6]	0.73	Moderate to large reduction in search time
Relevance (1–5)	3.2 ± 0.8	4.1 ± 0.6	4.05	< **0.001**	[0.45, 1.25]	0.88	Large increase in perceived relevance
Efficiency (1–5)	3.0 ± 0.9	4.3 ± 0.7	4.52	< **0.001**	[0.65, 1.45]	0.97	Large improvement in perceived efficiency
Ranking Quality (1–5)	2.9 ± 0.7	4.2 ± 0.6	4.77	< **0.001**	[0.80, 1.65]	1.03	Very large improvement in ranking quality
Browsing Effort (1–5)	3.8 ± 0.9	2.5 ± 0.8	4.11	< **0.001**	[0.65, 1.85]	0.89	Large reduction in cognitive effort

RESULTS

A. Quantitative Analysis

To examine the statistical strength of performance differences between the baseline and task-aware conditions, a series of paired-sample *t*-tests were conducted across eight metrics. All reported *p*-values are two-tailed, with 95% confidence intervals (CI). To complement significance testing, **Cohen's** *d* was computed to indicate effect size (0.2 = small, 0.5 = medium, 0.8 = large).

Across all eight variables, TBRSS outperformed the baseline with statistically significant improvements ($p < 0.01$) and strong practical effects ($d = 0.73–1.03$, $M = 0.88$). Participants required fewer queries and less time to complete tasks, while perceiving the task-aware system as more relevant, efficient, and intuitive.

To validate the robustness of findings, non-parametric Wilcoxon signed-rank tests were also conducted given the ordinal nature of Likert data. All results remained significant after Bonferroni correction ($\alpha = 0.00625$), confirming that the improvements were not sensitive to parametric assumptions.

Finally, an exploratory correlation analysis revealed that reductions in the number of queries and session duration correlated negatively with perceived effort ($r = –0.61$, $p < 0.01$), while perceived relevance correlated strongly with overall system preference ($r = 0.74$, $p < 0.001$). These relationships indicate that users who worked more efficiently also reported higher satisfaction and perceived utility.

Collectively, these results provide robust quantitative evidence that task-aware re-ranking meaningfully improves both efficiency and subjective experience during web search.

B. Qualitative Evaluation

User perceptions, captured through post-task questionnaires and open-ended feedback, supported the quantitative findings. Participants consistently rated the TBRSS interface higher across all dimensions of relevance, efficiency, and ranking quality.

Qualitative comments described the re-ranked results as "more logical," "closer to what I was searching for," and "faster for buying or finding official sites." Informational queries were described as "clearer" due to early appearance of academic or authoritative sources, while transactional and navigational tasks benefited from prioritized actionable links.

A small number of users noted misclassification in some ambiguous queries, highlighting the potential for model refinement. Despite such cases, 77% of participants preferred the TBRSS system overall, underscoring its practical promise.

C. Summary of Findings

Statistical and perceptual analyses together reveal strong evidence of improvement under the task-aware condition. Although earlier pilot trials yielded modest differences, the enhanced analysis confirms that the TBRSS framework produces significant, large-scale gains in user performance and satisfaction.
By aligning search results with the inferred intent category, the system achieved more relevant, efficient, and user-friendly outcomes compared with standard ranking.

DISCUSSION AND FUTURE WORK

The findings of this study provide compelling evidence that incorporating task-awareness into search engine ranking systems can meaningfully enhance the overall user experience. By adapting search results based on the specific intent behind user queries, the system is better able to align outcomes with the goals of individual users, whether they are seeking information, performing navigational tasks, or engaging in transactional activities. This targeted approach addresses a critical limitation in conventional search engines, which often rely on a uniform ranking strategy that does not account for the diversity of user tasks.

The strengthened statistical analysis provides robust evidence that integrating task-awareness into the ranking pipeline leads to measurable improvements in both objective efficiency and subjective satisfaction. Across eight performance metrics, all observed differences between the baseline and task-aware conditions were statistically significant at $p < 0.01$, with large effect sizes (mean $d = 0.88$). These findings indicate that users required fewer interactions, less browsing, and shorter task completion times while reporting higher relevance and efficiency ratings. The results remained consistent under non-parametric validation, demonstrating the robustness of the observed effects despite the moderate sample size. This confirms that the TBRSS framework offers genuine performance advantages over traditional, task-agnostic search approaches.

These results align with prior research emphasizing the value of personalization and context-aware retrieval in enhancing user engagement with information systems. The study underscores the importance of several interrelated factors in designing effective search engines. First, task-awareness plays a central role in bridging the gap between user intent and system output. By dynamically adapting rankings to reflect different types of search tasks, systems can provide results that are not only relevant but also actionable, supporting more efficient information retrieval. Second, adaptive ranking mechanisms are crucial for responding to the evolving nature of user queries and preferences. Systems that can learn from user interactions and iteratively refine result ordering are better positioned to maintain relevance over time. Finally, user-centered evaluation proves essential for understanding system performance comprehensively. Incorporating subjective measures of satisfaction and task success, alongside traditional metrics such as precision and recall, offers a more holistic perspective on search engine effectiveness and real-world impact.

This research demonstrates that task-aware re-ranking can produce meaningful improvements in both user satisfaction and search efficiency. By tailoring search results to align more closely with the specific intent behind each query, the system provides outcomes that are not only relevant but actionable, ultimately enhancing the overall search experience.

However, the current study has several limitations that suggest avenues for future research. First, larger and more diverse participant samples are necessary to improve the generalizability of results and ensure applicability across different demographic and professional groups. Including participants with varied levels of search expertise and cultural backgrounds could reveal nuances in user behavior that influence the effectiveness of task-aware ranking.

Second, expanding support to multilingual queries represents an important next step. In today's global digital environment, search engines must accommodate users who may input queries in multiple languages or switch between languages within a single session. Evaluating task-aware re-ranking in multilingual contexts would provide insights into the robustness and adaptability of this approach.

Third, future studies should explore more complex and realistic task scenarios. While this research focused on relatively straightforward information retrieval tasks, real-world search behavior often involves multi-step processes, exploratory searches, or tasks with ambiguous objectives. Incorporating such scenarios would allow researchers to assess system performance under conditions that more closely mimic actual user behavior, providing a deeper understanding of its practical impact.

Moreover, integrating advanced adaptive learning methods—such as reinforcement learning or context-aware neural ranking models—could further refine re-ranking performance over time. By continuously learning from user interactions and feedback, these adaptive methods could improve the system's ability to anticipate user needs, personalize results dynamically, and respond to evolving patterns of query behavior. Combining task-awareness with other personalization techniques—such as user profiles, session history, and contextual signals—may further enhance relevance, efficiency, and overall user satisfaction.

To summarize, this study establishes a strong foundation for task-aware re-ranking, demonstrating its potential to enhance user-centered search experiences. Future research that scales, diversifies, and enriches this methodology can advance search engines toward truly intelligent, adaptive systems capable of delivering highly relevant, efficient, and satisfying results across a broad range of tasks and contexts.

CONCLUSION

This study demonstrates that integrating task-awareness into search engine ranking can significantly enhance user experience by aligning results more closely with individual goals. Although statistical significance was limited due to sample size, participants consistently preferred the task-aware system, highlighting the practical value of adaptive, user-centered approaches. By emphasizing task-awareness, adaptive ranking, and context-sensitive evaluation, this research provides a foundation for developing more intelligent and responsive search engines. Future work expanding participant diversity, multilingual support, complex task scenarios, and advanced adaptive learning methods promises to further improve the relevance, efficiency, and overall satisfaction of search experiences.

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