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Applicability of Process Mining in Usability Tests: A Case Study for Identifying User Mental Models in Geospatial Search Engines

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ABSTRACT A fundamental challenge in digital product design is ensuring that actual mental models of users align with the intended functionality of the system. When discrepancies arise, usability can suffer, leading to inefficient interactions and reduced adoption. Usability testing lets development teams identify design problems in digital products by collecting qualitative and quantitative information. However, this technique is often not able to provide a panoramic view of the interaction with the system, especially when dealing with complex interfaces such as those used in geospatial search engines and we need to analyse the quantitative data compiled during testing. This work proposes to actively incorporate process mining into usability testing. We discuss the implications of process mining on usability testing using a case study performed at the National Geographic Institute of Spain, where a new geospatial search engine was under development. Twenty-one participants, ranging from novice to expert users, were recruited to perform a search task using the new geospatial search engine. The findings reveal that the mental model of users leans towards the archetype of a regular search engine rather than fully utilising the geographic functionalities provided by the platform, as intended by its designers.

INDEX TERMS Usability testing, User models, User studies, Geographic information systems

I. Introduction

In recent years, demand for geographic information has risen considerably [1]. To address the exponential growth of spatial data, various spatial data infrastructures have been created to improve accessibility and availability. Geospatial search engines are essential for the discovery of geographic data [2], [3], yet their interface design remains challenging [4]. Searching is a dynamic, user-driven process in which mental models must align with system functionalities to ensure satisfactory experiences. Although user mental models are known to be central in interface design [5], developers struggle to predict effective architectures or actual usage during early design stages.

Often, designers envision usage models that diverge from real user mental models, reducing usability. Usability testing helps identify design problems through qualitative and quantitative evidence but rarely offers a complete view of interaction. As Titus et al. [6] note, such methods have inherent limitations and benefit from complementary approaches.

Understanding user behaviour is a central concern not only during the early stages of a web platform—as is the focus of this research—but throughout its entire lifecycle. This sustained interest has motivated a substantial body of research [7]–[9]. Despite the valuable insights generated by this literature, a persistent research problem remains: there is a lack of systematic, process-oriented methods for organising

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and interpreting empirical findings about user behaviour in a way that meaningfully links observed interaction patterns to underlying cognitive constructs such as user mental models. Although human behaviour in interactive systems is inherently dynamic and context-dependent, yet many evaluation approaches still rely on static metrics or isolated observations that fragment this complexity.

As a result, researchers and practitioners face difficulties in coherently synthesising heterogeneous usability evidence and in translating it into actionable design knowledge. In this context, the well-established theory of mental models in human–computer interaction, together with advances in process mining, offer complementary concepts and analytical tools that can help structure interaction data more effectively. Their combined use holds particular promise for transforming raw interaction logs into interpretable representations of user behaviour that can be systematically compared with design assumptions across the lifecycle of complex web platforms.

This work proposes a framework for integrating process mining into the usability testing of geospatial search engines—and, by extension, other complex web platforms. A key advantage is the availability of visualisation tools to infer user mental models and deviations from design concepts. We demonstrate feasibility through a case study at the National Geographic Institute of Spain (IGN), a key actor in the Spanish spatial data ecosystem. The new geospatial search engine was motivated by the need to integrate diverse information sources. Data were collected via a usability test in which twenty-one participants, from novices to experts, performed search tasks. Their interactions were logged and analysed using process mining, descriptive, and inferential statistics. Findings showed that user mental models resembled those of general search engines, underutilising the geographic functionalities intended by designers.

Building on prior research applying process mining to search tasks [10], this study reflects on its potential and challenges within usability testing, before, during, and after experiments. It broadens the analytical scope to include usability scores, control flow, textual search, filters, and results, offering a more holistic understanding of search experiences. Moreover, the principles derived are applicable to other search engines with similar features. Case studies providing such comprehensive evaluations can guide practitioners facing the challenge of designing satisfactory interfaces in related domains [11], [12].

II. Related work

A. Usability testing

Usability is the "extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use" [13]. Closely related is user experience, defined as the "perceptions and responses that result from the use and/or anticipated use of a system, product or service" [13]. Improving usability in interactive systems is the focus of usability engineering [14]. Since the early 1980s, evaluation methods have evolved considerably [15], [16]. They are typically divided into inspection methods (e.g. heuristic evaluation, cognitive walkthroughs), which do not involve users directly, and user-based methods such as usability testing, surveys, interviews, focus groups, and field studies. Although more costly, usability testing is widely recognised as more effective in detecting severe and recurrent problems than inspections [17].

In usability testing, a moderator guides participants through predefined tasks while observing behaviour and collecting feedback [18]. This process uncovers design issues, opportunities for improvement, and insights into user preferences. The most common approach is the think-aloud protocol, where participants verbalise their thoughts in real time while using the system [19].

Usability testing may be qualitative or quantitative [20]. Qualitative approaches gather narrative evidence to uncover problems, while quantitative methods collect metrics for benchmarking. Combining both provides richer insights, with the balance depending on the stage of development: early tests often stress quantitative data, whereas later ones prioritise qualitative insights [21].

Most accounts of usability testing describe a common procedure [22]–[25]: (i) planning (purpose, objectives, product, participants, metrics), (ii) preparation (recruitment, environment), (iii) execution (user interaction and data collection), and (iv) analysis and reporting. Standard metrics address effectiveness (e.g. task completion rate), efficiency (e.g. task execution time), and satisfaction, commonly measured through the Smiley scale [26] or the System Usability Scale (SUS) [27]. Qualitative data, in turn, provide explanations for these metrics [20].

The usability of Geographical Information System (GIS) applications has been the subject of several studies. Unlike conventional interfaces, GIS usability is strongly shaped by the map [28]. A systematic review by Kurniawan et al. [29] found usability testing to be the most used method, followed by inquiry methods based on self-reported experiences, often with SUS [30]–[32]. Inspections were less frequent, while eye- and mouse-tracking have also been employed to assess map interface design [33]. Common usability issues include inadequate user guidance, tool use challenges, and interface design flaws. Overall, further methodological development is needed to analyse GIS-specific interactions and workflows [28], [34].

B. Process mining

Process mining bridges process models and event data, acting as a link between process and data science [35]. Three core types are distinguished [36]: (a) process discovery, which learns models from event logs; (b) conformance checking, comparing observed with prescribed behaviour; and (c) model enhancement, which repairs or extends models.

Additional dimensions include control flow (sequence of activities), organisational (resources and actors), case (properties of individual cases), and time (frequency and timing of events). These dimensions are not mutually exclusive but provide a flexible, multidimensional view of processes [37].

Process mining relies on event logs, which follow four assumptions: processes consist of cases, cases of events, each event belongs to one case, and events are ordered with attributes [35]. Typical logs contain case, activity, and timestamp, with optional attributes such as resource or cost. Results are often presented visually, with tools such as directly-follows graphs, Petri nets, process trees, dotted charts, variant diagrams, and matrices [38].

The integration of process mining and usability engineering is known as usability mining [39], [40]. Thaler [39] explored automated usage models to quantify usability in business systems, while Dadashnia [40] applied usability mining to mobile policing applications in Germany.

C. Mental models in human-computer interaction

Mental models are mechanisms by which individuals describe goals and design, explain system dynamics, and predict future states [41]. Widely studied since the 1980s [42], they remain difficult to measure and represent in modern applications [43].

During the design of information systems, it is key to differentiate between the mental model of designers, often referred to as the conceptual model, and the mental model of users [44]. In the case of the conceptual model, it involves having a conceptual representation of the intended system and transforming those ideas into a tangible implementation. On the other hand, the mental model of users acknowledges their actual knowledge about the system, which is influenced by their cognitive abilities, past experiences, problem-solving strategies, and individual variances. Designers frequently possess intricate mental models of their own creations, which can lead them to believe that every feature is intuitively understandable [45].

Different conceptualisations of mental models exist. Component models describe structure, while causal models explain cause–effect dynamics [46]. Carroll and Olson [44] further distinguish surrogates, metaphors, crystal boxes, and networks. Understanding user models aids interface design and training: aligned designs ease learning and reduce errors, while misaligned ones require training and guidance. Jakob's Law reinforces this, noting that users expect familiar design patterns [47].

Mental models are typically elicited through verbal accounts [48], drawings [49], or error observation [50], often combined with think-aloud methods. Despite decades of research, applications of mental models continue to diversify, calling for further conceptual and methodological development [51].

D. The information-search process

In this case study, mental models are examined within information search. Hearst [52] compiles several models, with the standard and dynamic models most relevant to short-term tasks. The standard model describes a cycle of need recognition, query specification, result review, and reformulation [53]–[57]. This assumes static information needs. However, studies show search is dynamic: needs evolve as users learn and refine questions [58]. The berry-picking model introduced by Bates emphasises shifting queries and satisfaction gained incrementally rather than from final results [59]. In practice, many users exhibit a "Google-like" effect [60]–[62], preferring simple search engines over specialised systems, even when the latter offer richer functionality.

III. Methodological framework

Our framework integrates usability testing, mental modelling, and process mining. The key contribution is showing where process mining can be embedded in a conventional mixed-methods usability test to analyse mental models without overcomplicating the study.

As shown in Figure 1, the framework has four phases. First, examine the target system to identify its conceptual model and activities to mine. Second, design and run a search task with representative users while recording interactions. Third, analyse mined interactions to detect patterns that inform users mental models. Fourth, compare the systems conceptual model with the inferred mental model to locate mismatches. The aim is to guide interface improvements. This approach follows observational elicitation with a think-aloud protocol.

A. Examination of the target system to identify its conceptual model

Understanding the conceptual design involves interviews with product and development teams and a review of technical documentation (feasibility, analysis, design, construction, and implementation guides) and the user interface.

The conceptual model is typically mixed, combining a search engine and a GIS (Figure 2). The goal is to couple flexible search with rich geographic context, not merely aggregate features. Integration must feel seamless and intuitive.

B. Design and execution of a search task with representative users

Sessions follow pre-test, test, and post-test stages (Figure 3). Participants sign informed consent and complete a pretest questionnaire to confirm category. Consent covers objectives, methods, withdrawal, and data safeguards.

Participants are evenly allocated to three categories:

1) Novice users: This category includes people with no academic background or relevant professional experience in geography or related disciplines and who are not regular users of the geographic information platforms of the institute.

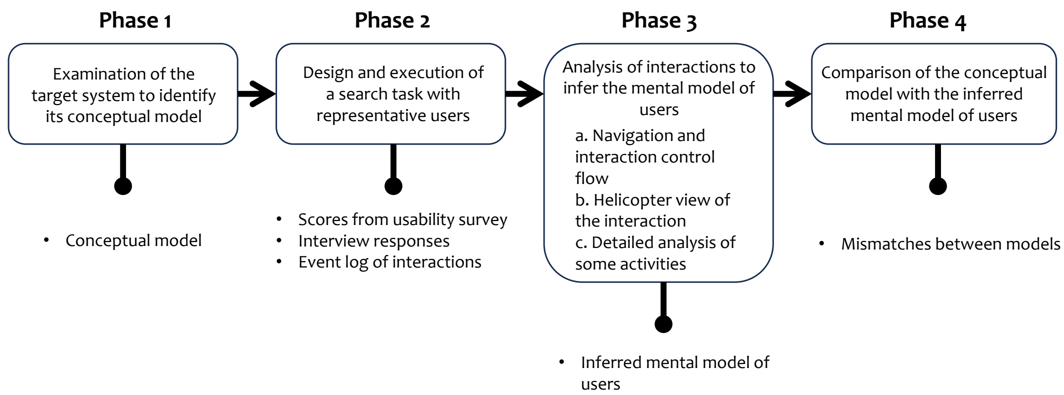


FIGURE 1. **Methodological framework at a glance.**

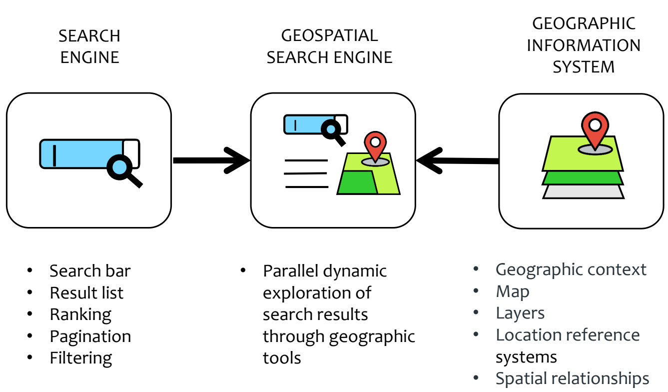


FIGURE 2. **Conceptual model of a geospatial search engine.**

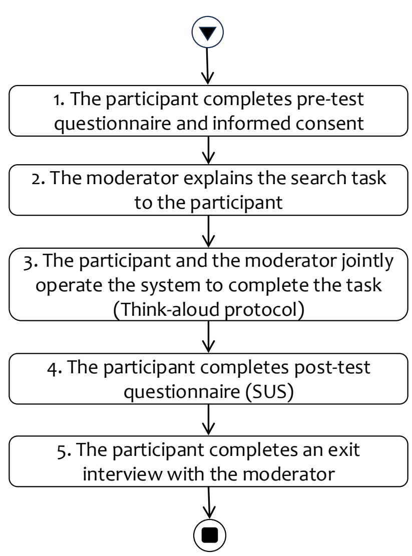


FIGURE 3. **Flowchart representing the test workflow.**

2) Expert unfamiliar users: This category includes people with relevant academic training or professional experience in geography or related disciplines who are not regular users of the geographic information platforms of the institute.
3) Expert familiar users: This category includes people with relevant academic training or professional experience in geography or related disciplines who are regular users of the geographic information platforms of the institute.

The categorisation is driven by the hypothesis that domain expertise and familiarity with specific conventions, such as those embedded in the platforms of a particular data publisher, can influence behaviour and mental models. Rather than maximising statistical power for hypothesis testing, this grouping was designed to ensure that meaningful user profiles were adequately represented, enabling comparative, process-oriented analyses through process mining. At this stage, balanced group sizes support the visual and qualitative comparison of control-flow structures, interaction variants, and temporal patterns, which form the primary analytical basis for identifying systematic differences in how users conceptualise and navigate the search task. Recruitment used referral sampling [63]. The study complies with the EU Horizon 2020 Ethics Appraisal Procedure, including clear inclusion procedures and informed consent.

Each session ends with the System Usability Scale (SUS) and a short exit interview. SUS has 10 items on a 5-point scale and yields a 0–100 score [27].

C. Analysis of interactions to infer mental models of users

After the sessions, we create an event log with case, activity, and timestamp, stored as CSV. Analysis combines process mining with descriptive and inferential statistics.

We begin with the **control flow**, generating directly-follows graphs to characterise page transitions and activity execution [35]. Next, we offer a **helicopter view** using dotted charts and a variant explorer to summarise sequences and variability. We subsequently examine participants use of search terms and filters. Finally, given the geospatial nature of the system, we present a **detailed analysis of key activities**—querying, filtering, and interaction with search results.

Results are segmented by user category. Where relevant, ordinary least squares regression assesses the effect of user group on SUS, activity counts, session duration, and perceived relevance of results, with gender, age, and education as one-hot encoded controls; novices are the reference group. Significant differences are marked with asterisks in figures and tables.

D. Comparison of the conceptual model with the inferred mental model of users

We compare the systems intended design logic and structure (from documentation and team interviews) with mental models inferred from interactions and feedback. Misalignments reveal incorrect assumptions, misunderstandings, or gaps in how the system is perceived. These discrepancies often underlie usability issues and inefficiencies. The comparison guides targeted interventions: clearer feedback and visibility, closer alignment of interface metaphors with expectations, and improved onboarding. Iterative refinements then ground design decisions in both the conceptual architecture and users lived experience.

IV. Experiments and Results

A. Examination of the target system

Under the Linked Cartography project, IGN created a geospatial search engine that consolidates around two million resources previously scattered across IGN platforms [64]. A core objective is to broaden access beyond specialist audiences. Figure 4 shows three navigation levels: (a) “Quick search”, (b) “Advanced search & results”, and (c) “Metadata”.

On the “Quick search” page, a text bar serves as the entry point, with a link to advanced geographic search (points, polygons, geometry files, coordinates, and cadastral references) and thematic filters. Submitting a search leads to the “Advanced search & results” page, which lists results with actions (view, download, purchase, locate), offers faceted filters, and shows a map for spatial context and interaction. Selecting a resource opens the “Metadata” page with details and actions. Some activities can be performed on more than one page.

The mixed design is explicit on the “Advanced search & results” page: the left side follows a search engine archetype (keyword entry and vertical results list [52]); the right side reflects a GIS archetype with a dominant map [65].

B. Design and execution of a search task with representative users

IGN engaged partners to recruit participants. Table 1 reports 21 participants by gender, age, and education.

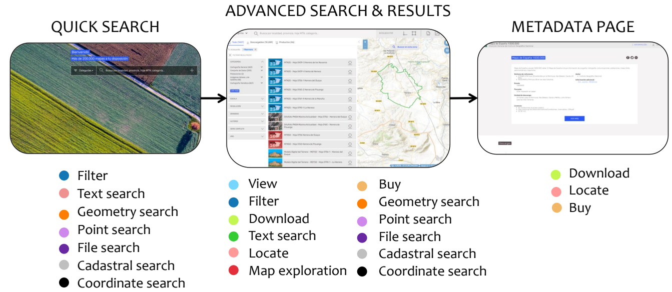


FIGURE 4. Geospatial search engine interface.

TABLE 1. Participant demographics, n (%).

	All	I. Novice users	II. Expert unfamiliar users	III. Expert familiar users
Gender				
Male	11 (48%)	4 (57%)	3 (43%)	4 (57%)
Female	10 (52%)	3 (43%)	4 (57%)	3 (43%)
Age				
18-24	1 (5%)	1 (14%)	- (0%)	- (0%)
25-34	5 (24%)	1 (14%)	2 (29%)	2 (29%)
35-44	3 (14%)	- (0%)	1 (14%)	2 (29%)
45-54	10 (48%)	3 (43%)	4 (57%)	3 (43%)
54-65	2 (10%)	2 (29%)	- (0%)	- (0%)
Education				
High School	1 (5%)	1 (14%)	- (0%)	- (0%)
Graduate	15 (71%)	5 (71%)	3 (43%)	7 (100%)
Postgraduate	5 (24%)	1 (14%)	4 (57%)	- (0%)
Total	21	7	7	7

The task reflects common tourism queries: plan a trip to Sierra Nevada National Park and use the engine to find, download, or collect useful products. Sessions were video recorded, and a browser extension logged clicks and timestamps. Click logs could not reliably map to actions due to label ambiguity, so the moderator annotated data manually.

SUS was administered after each test; Cronbachs $\alpha = 0.77$ indicates reliability. Table 2 shows item and total scores. Controlling for gender, age, and education, user category significantly affected SUS: expert familiar users reported lower scores than the other groups, with significant differences on items 2, 5, 7, and 8.

Figure 5 maps scores to adjective and acceptability ratings. Novices and unfamiliar experts lie near the marginal boundary, whereas familiar experts trend towards non-acceptable or marginal zones [66]. Prior GIS studies report a wide SUS range from not acceptable [31] and marginal [32] to acceptable [30].

TABLE 2. SUS scores for each item and testing group.

SUS items	All	I	II	III	
	Average score contribution (0-4)				
1. I think that I would like to use this system frequently	2.8	2.7	3.0	2.6	
2. I found the system unnecessarily complex	2.3	3.0	2.4	1.4	***
3. I thought the system was easy to use	2.8	2.6	3.0	2.9	
4. I think that I would need the support of a technical person to be able to use this system	3.0	2.6	3.4	3.0	
5. I found the various functions in this system were well integrated	2.6	3.1	2.7	1.9	***
6. I thought there was too much inconsistency in this system	2.3	2.4	2.6	1.9	
7. I would imagine that most people would learn to use this system very quickly	2.2	3.3	2.4	1.0	***
8. I found the system very cumbersome to use	2.9	3.1	3.6	2.0	**
9. I felt very confident using the system	2.6	2.9	2.4	2.4	
10. I needed to learn a lot of things before I could get going with this system	2.9	2.6	3.3	2.7	
SUS Score (0-100)	65.7	70.7	72.1	54.3	**

*, **, *** significant at p ≤ 0.10, 0.05 and 0.01 respectively.

0 1 2 3 4

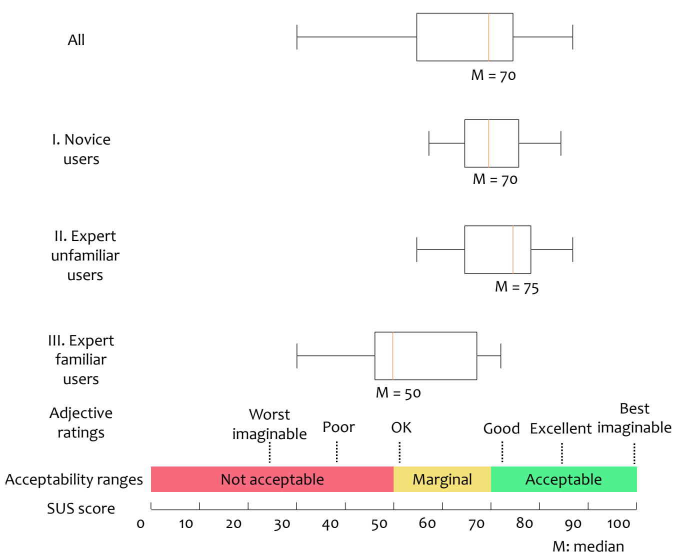


FIGURE 5. Box plots of SUS scores for each testing group.

C. Analysis of interactions

Code and notebooks are available in a public repository[1]. Logs were processed with PM4PY; charts were produced with PMTK; Disco [67] generated directly-follows graphs.

1) Navigation and interaction control flow in the geospatial search engine

Directly-follows graphs [68] summarise navigation (Figure 6). Sessions start on "Quick search", move quickly to "Advanced search & results", and iterate with "Metadata". Vertex labels show mean time per page; edge thickness shows transition frequency.

Figure 7 adds action nodes (blue) to pages (green). Edge thickness and node saturation reflect frequency. Less frequent edges are pruned to reduce spaghetti-like complexity. The main path begins with text search, continues with viewing and filtering on "Advanced search & results", and performs download, locate, and buy on "Metadata". Subgroups follow the same pattern.

[1]https://github.com/IAAA-Lab/Applicability-of-process-mining-in-usability-tests-ODECO-IGN

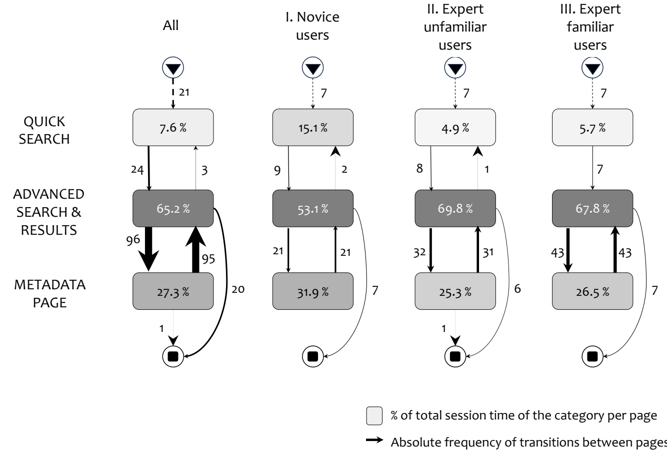


FIGURE 6. Navigation process map.

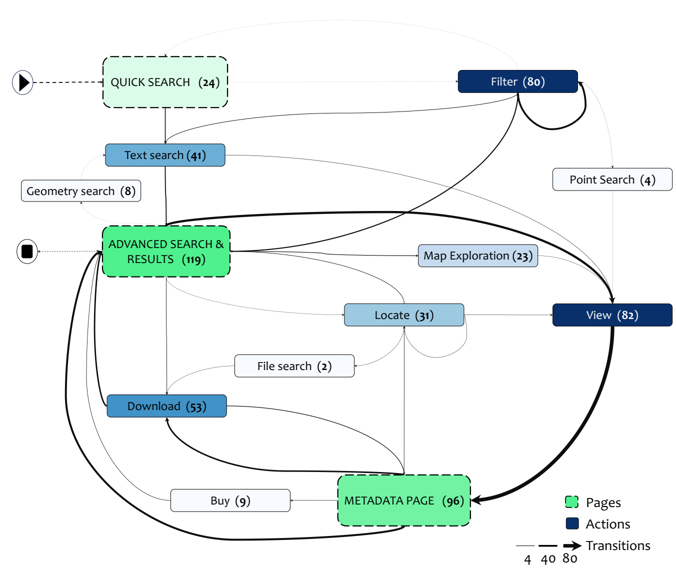


FIGURE 7. Search process map including pages and actions for all participants.

2) Helicopter view of the interaction

Figure 8 shows sessions as dotted charts by absolute time. We observe wide variation in duration ($mean = 22'18''$, $median = 20'42''$, $sd = 10'18''$, $max = 44'06''$, $min = 7'42''$) and interaction counts ($mean = 15.9$, $median = 16$, $sd = 7.3$, $max = 30$, $min = 6$). Regression indicates novices had shorter sessions and fewer interactions.

Figure 9 reports mean interactions by activity and group (left) and dot plots by relative time (right). No group differences were significant at $p < 0.05$ except for view, where novices viewed fewer resources than expert familiar users. A representative profile shows view and filter about four times each, download three times, text search twice, and map exploration and locate once. Geometry, point, file, cadastral, and coordinate searches were rarely or never used. Timing varies by activity.

Figure 10 presents a variant explorer and a relative timeline. Sequences are diverse with few reusable patterns. Most

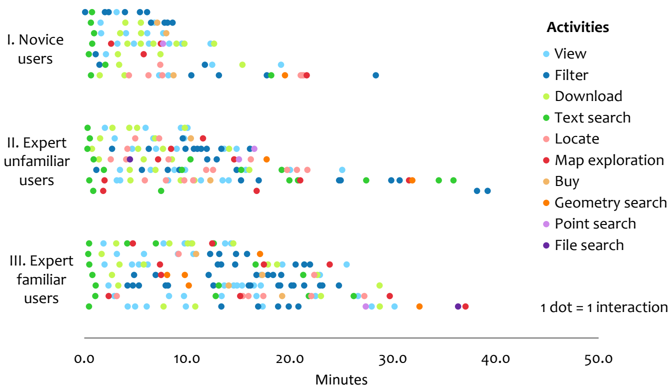
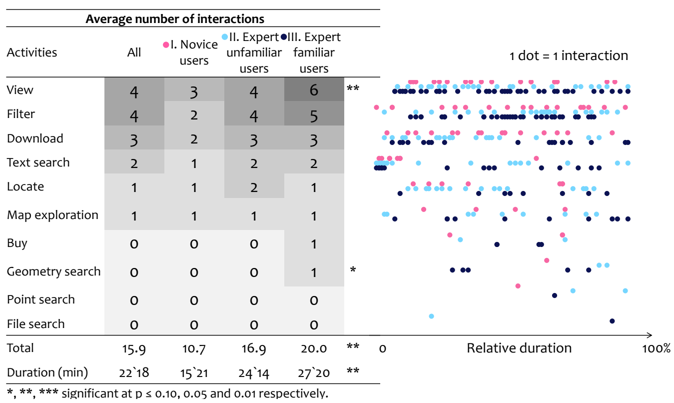


FIGURE 8. **Dotted chart distribution of the events over absolute time.**



Activities	All	I. Novice users	II. Expert unfamiliar users	III. Expert familiar users	
	Average number of interactions				
View	4	3	4	6	**
Filter	4	2	4	5	
Download	3	2	3	3	
Text search	2	1	2	2	
Locate	1	1	2	1	
Map exploration	1	1	1	1	
Buy	0	0	0	1	
Geometry search	0	0	0	1	*
Point search	0	0	0	0	
File search	0	0	0	0	
Total	15.9	10.7	16.9	20.0	**
Duration (min)	22`18	15`21	24`14	27`20	**

*, **, *** significant at p ≤ 0.10, 0.05 and 0.01 respectively.

FIGURE 9. **Dotted chart distribution of the events over relative time.**

sessions begin with text search, sometimes followed by filter; advanced search was not used on "Quick search". Several traces end with filters without subsequent resource exploration. Timelines suggest text search early, with view, locate, and download occurring in the first half; map exploration and filters appear later.

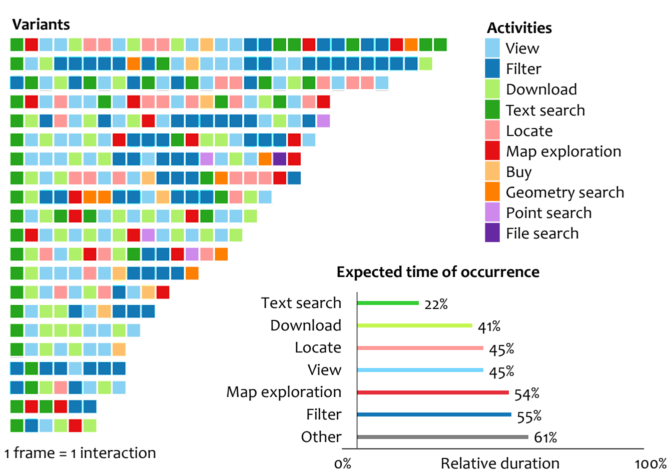


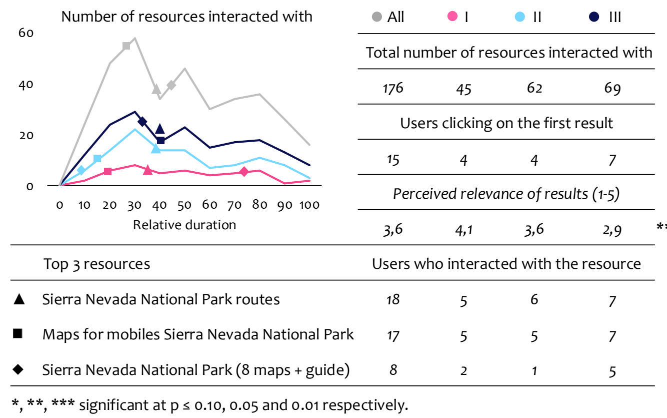
FIGURE 10. **Variants explorer sequence of events.**

3) Detailed analysis of some activities

We examined query terms, filtering, and results. Of 41 text searches, 83% explicitly mentioned the park; a few used nearby place names; none used natural language.

Among 80 filter interactions, 78% targeted thematic category; other filters were seldom used, and participants reported difficulty due to long lists.

Participants engaged with 46 distinct resources across view, locate, download, and buy. No time limit or success list was enforced. Figure 11 summarises resource interaction. Expert groups peaked earlier (within the first 20–30% of session progress); novices were more evenly distributed. Novices interacted with fewer resources and clicked the first result less often but rated relevance higher. The three most accessed resources were routes, mobile maps, and a map set with guide, typically accessed in the first half of sessions.



	All	I	II	III	
Total number of resources interacted with					
	176	45	62	69	
Users clicking on the first result					
	15	4	4	7	
Perceived relevance of results (1-5)					
	3,6	4,1	3,6	2,9	**
Top 3 resources	Users who interacted with the resource				
▲ Sierra Nevada National Park routes	18	5	6	7	
■ Maps for mobiles Sierra Nevada National Park	17	5	5	7	
◆ Sierra Nevada National Park (8 maps + guide)	8	2	1	5	

*, **, *** significant at p ≤ 0.10, 0.05 and 0.01 respectively.

FIGURE 11. **Interaction with resources found by participants.**

D. Model comparison

At a metaphorical level, the conceptual model blends search engine and GIS paradigms, but the inferred mental model is more search centric, consistent with prior work [60]–[62]. Expert users align more closely with the conceptual design; novices show greater deviation. All groups reflect stages of the standard search model; download and purchase occur mainly on "Metadata" after evaluation. Dynamic behaviours are rare, likely due to the focused task. Experts interact more and browse more resources, approaching the hybrid vision but with less ease than intended; novices follow linear paths and underuse spatial tools. Most users still found relevant material.

Behaviour suggests a Pareto-like pattern [69]: a few functions dominate use. This supports prioritising core flows while reassessing underused features. The map, despite prominence, drew less attention than expected, prompting a review of its role. File, cadastral, and coordinate searches may warrant de-emphasis if general-purpose search is prioritised.

The persistent underuse of advanced search options could be interpreted as the result of an interplay between multiple factors such as prior experience, interface salience, and task context. Interaction patterns suggest that user mental models are strongly shaped by exposure to general-purpose search engines, leading them to prioritise simple keyword-based search even when more powerful spatial tools are available. In addition, advanced search options, such as coordinate, cadastral, or geometry-based queries, entail a higher cognitive cost and require domain-specific knowledge, which may discourage exploration when these options are not perceived as a natural extension of the primary search flow. Process mining analyses further revealed that advanced options were not only infrequently used, but systematically bypassed early in the interaction sequence, indicating that users quickly committed to simpler strategies. Finally, careful consideration must be given to the impact of the selected search task: although the tourism-oriented scenario aligns with one of the intended use cases of the platform, it lacks an organic connection to cadastral references and similar professional queries. As a result, the minimal use of cadastral search options is not unexpected, highlighting how task framing can shape observed interaction patterns.

SUS and relevance ratings differ by group: familiar experts rated the system lower. Differences may reflect factors beyond the interface, such as self-assessment biases, and motivate further hypotheses.

V. Discussion

A. Reflections on process mining in usability testing

When considering the respective purposes of usability testing and process mining, their complementarity becomes clear. Usability testing aims to gather direct feedback on how real users interact with a system, whereas process mining is designed to reconstruct and analyse actual behavioural processes through data-driven modelling and visualisation. The event-driven nature of usability testing therefore lends itself naturally to the application of process mining techniques. This complementarity is reflected, for instance, in the observed contrast between insights derived from process mining analyses and those obtained from traditional usability perception questionnaires. While commonly reported usability metrics are valuable, they remain limited in their ability to explain how and why specific interaction paths unfold [20], a gap that process mining is particularly well suited to address. This broader analytical perspective is especially beneficial in systems that afford users a high degree of freedom, as was the case with the geospatial search engine examined in this study.

However, integrating process mining into usability testing introduces a number of methodological challenges that must be addressed before, during, and after the test. Compared to standard usability evaluations, additional effort is required at the preparation stage, particularly in defining the product under study. As demonstrated by the case study, preparation involves not only selecting and configuring the system, but also making explicit the assumptions of designers about the intended use and identifying potentially usability-relevant activities. A critical challenge at this stage lies in determining an appropriate level of activity granularity that aligns with the interests of stakeholders seeking to improve the system. Importantly, this mapping should not be seen as definitive; rather, it serves as a sensitising step that prepares researchers to recognise relevant activities that may emerge during testing but were not initially anticipated.

During test execution, careful consideration must be given to the mechanisms used for recording interaction events. In the present study, user sessions were video-recorded and later manually annotated. Although this approach enables a detailed reconstruction of user behaviour, it is both time-consuming and prone to error due to its manual nature. Prior research has similarly highlighted the practical challenges associated with manual video transcription for identifying user activities [40]. After data collection, analysis requires expertise in data manipulation and familiarity with process mining techniques. While usability testing typically does not generate massive datasets [70], the analytical demands remain non-trivial. Nevertheless, the growing availability of user-friendly open-source and proprietary tools—such as PM4Py and PMTK, alongside commercial solutions like Disco—helps to lower the barrier to adoption.

Beyond the specific case of geospatial search engines, the framework proposed in this study is intentionally domain-agnostic. Rather than relying on domain-specific interaction semantics, it builds on general principles of usability testing, structured event logging, and process mining. As such, it is well suited to domains in which discrepancies between conceptual models and user mental models are known to recur. A closely related application domain is that of data portals [71], typically organised around rich metadata schemas and advanced query mechanisms that distinguish them from conventional websites. In such contexts, reliance on mental models shaped by general-purpose search engines may lead to the underutilisation of advanced features.

Similar misalignments can be observed in domains where domain expertise plays a central role, such as healthcare portals [72]. In these systems, conceptual workflows can be expected to be structured around institutional or clinical processes, whereas users—particularly patients—may be inclined to adopt episodic and goal-oriented navigation strategies that prioritise immediate information needs. This mismatch frequently may result in fragmented interaction paths and the bypassing of prescribed workflows. Even in broader domains such as e-commerce, where domain expertise may be less prominent, assessing user mental models remains important, as dissonance may arise from cultural factors, prior exposure to dominant interface paradigms, or expectations shaped by other platforms [73].

B. Reflections on the geospatial search engine use case

This section revisits the main problems articulated in the introduction and discusses how the empirical results of the usability test augmented with process mining.

A core challenge identified in the introduction concerns the difficulty of ensuring alignment between conceptual models and user mental models in complex digital systems, particularly those that integrate heterogeneous interaction paradigms such as search engines and GIS interfaces [44]. The results of the case study provide empirical evidence of this challenge. Although the IGN search engine was intentionally conceived as a hybrid system (combining ranked textual search with spatial exploration) the observed interaction processes show that users predominantly enact a general-purpose search engine mental model, privileging keyword-based queries and linear result inspection while largely bypassing advanced geographic search functionalities.

Process mining plays an important role in making this misalignment explicit. Traditional usability instruments, such as SUS scores and post-test interviews, indicated moderate usability issues and perceptual differences between user groups, particularly with respect to expert familiar users. However, these instruments alone offer limited explanatory power regarding how such issues emerge during interaction [6], [34]. By contrast, process mining reconstructs complete interaction trajectories, revealing that advanced options (e.g., coordinate, cadastral, or geometry-based searches) are not merely underused, but systematically bypassed early in the interaction sequence. This finding directly addresses the introductory problem of fragmented usability evidence by linking observed outcomes to concrete behavioral processes.

The results further align with prior research on information-seeking behavior and mental models. The dominance of simple keyword search reflects the well-documented influence of the prior exposure to general-purpose search engines, often described as a “Google-like” mental model [60]–[62]. Jakob’s Law reinforces this interpretation, suggesting that users transfer expectations from familiar systems to new interfaces, even when richer functionality is available [47]. From this perspective, the underutilization of advanced geospatial features is not an anomaly, but a predictable consequence of established interaction habits combined with the higher cognitive cost associated with specialized query modes [52], [59].

These findings have direct and actionable implications for the IGN development team. First, the consistent reliance on text-based search suggests that core search workflows should be explicitly optimized and treated as primary interaction paths, rather than assuming that users will naturally transition to spatial or advanced modes. Second, the relatively limited engagement with the map—despite its central visual role in the interface—indicates a need to reassess its functional integration. Prior work on GIS usability highlights that maps do not automatically function as intuitive exploratory tools unless their affordances and benefits are clearly communicated [28], [33]. Third, the minimal use of professional-oriented search options, such as cadastral or coordinate-based queries, suggests that these features may require clearer contextual cues, onboarding mechanisms, or strategic repositioning when the platform targets non-specialist audiences.

The study also clarifies what should occur after the usability test. Rather than serving as a one-off evaluation, the resulting process models provide a behavioral baseline that can inform iterative design. For IGN developers, this enables a concrete post-test roadmap: redesigning interaction flows, conducting follow-up usability tests, and applying process mining techniques such as conformance checking or model enhancement to assess whether revised interfaces reduce the gap between intended and observed behavior [74]. In this sense, process mining supports a continuous, evidence-based design cycle that extends the value of usability testing throughout the lifecycle of the system.

C. Limitations

The limitations include a relatively small sample size, which is appropriate for identifying recurring patterns in usability and interaction behaviour but limits the robustness of group-based inferential comparisons. The usability literature suggests that many usability issues can be uncovered with small samples using think-aloud protocols [18], [75], although this remains an active area of debate [76]–[78]. In this study, dividing participants into three conceptually meaningful groups further constrains the statistical power, particularly for detecting small or moderate effects. Consequently, inferential analyses are intended to provide a complementary and exploratory role, supporting and contextualising the primary findings rather than enabling strong generalisation. The main contributions of the study are therefore descriptive and process-oriented, relying on process mining visualisations and interaction patterns to infer user mental models and identify systematic mismatches with the conceptual design.

A further limitation concerns the manual annotation of event logs. In practice, annotation ambiguity was minimal, as events were mapped to a predefined and explicit set of user interface actions, each one associated with clearly identifiable interface elements and interaction types. This action taxonomy was defined during the examination of the target system phase and provided a stable reference for coding user behaviour. Inter-rater reliability was not formally assessed because the annotation was conducted by a single trained researcher. In addition, the constrained and interface-driven nature of the action set reduced subjective interpretation and supported consistent application across sessions. However, while predefined actions reduce ambiguity, they may also limit the opportunity to capture unforeseen fine-grained behaviours that reflect hesitation, misunderstanding, or exploratory interaction. The remaining sources of error include minor temporal imprecision in timestamp assignment or occasional misclassification. Automatic annotation strategies could further minimise this residual noise by improving the consistency and reproducibility of event recording, thereby facilitating broader adoption of the framework and allowing practitioners to focus on higher-level, strategic aspects of evaluation.

Additionally, moderator presence may have lengthened sessions or encouraged complex operations, especially for experts, yet think-aloud yielded insights essential for interpreting behaviour. Task choice also matters: a tourism scenario weakens the case for cadastral searches, explaining their rarity.

VI. Conclusions

We explored how process mining can reveal users mental models during design of a geospatial search engine. Using a case study at IGN, we recorded sessions, built event logs, and applied process mining with descriptive and inferential statistics. Observed mental models leaned towards a general search engine rather than a GIS, diverging from the intended hybrid model.

Future work includes improving automatic event logging and mapping low-level events to meaningful activities [8]; extending beyond discovery to conformance checking with metrics such as fitness [74]; and building real-time, personalised support for users with inadequate mental models.

As new interfaces proliferate, we hope this work encourages further use of process mining in usability testing and advances mixed quantitative–qualitative tools for analysing and visualising mental models in human–technology interaction.

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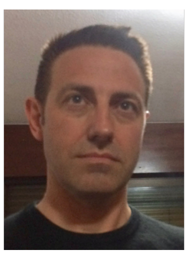

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