User interaction mining: discovering the gap between the conceptual model of a geospatial search engine and its corresponding user mental model

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Abstract. Designers often project into their creations usage models that attempt to idealise and anticipate how users will interact with the future system. However, these conceptual models do not always match the actual mental models of users. This mismatch may result in sub-optimal functioning that negatively impacts user experience. Discovering these deviations, especially in early design stages, could serve to align the system to the existing mental models or to train users appropriately for new paradigms. This paper reports on work in progress addressing the challenge of discovering models of user behaviour from usability tests on user interfaces. We present a case study performed at the Spanish National Geographic Institute, where a new geospatial search engine has been developed. Twenty-one participants, including novice and expert users, were recruited to perform a search task with the new geospatial search engine. The interactions mined were recorded as event logs and analysed with process mining techniques, descriptive and inferential statistics. The results indicate that the mental model of users is biased toward the archetype of a regular search engine, rather than taking advantage of the geographic functions provided by the platform, as intended by the designers. This case study illustrates the potential that interaction mining can add to the design and evaluation of new user interfaces.

Keywords: Geospatial portal · User interface · Mental model · Interaction mining · Process mining.

1 Introduction

The use of geographic information has increased exponentially in the last decades. To manage this explosion of data, spatial data infrastructure (SDI) initiatives were launched to facilitate the availability and access to spatial data. Geospatial search engines are crucial for searching and discovering geographic information resources in SDIs [10]. Designing these search interfaces is a challenge. Information search is a complex user-centred process where the functionalities of the information system and the mental models of the user must interact in alignment to produce satisfying experiences. It is difficult for developers to know in advance, during the design and development stages, what will be the most effective information architecture or how the system will be used in reality.

The objective of this paper is to propose a methodology to identify the gap between the design of a geospatial search engine, and the mental models gained by users during the interaction with these search engines. It is known that user mental models help to design or refine the design of user interfaces.

In particular, we have proposed this methodology to evaluate and improve the design of the new geospatial search engine of the National Geographic Institute of Spain (IGN). The institute is the coordinator of the Spanish SDI and the main producer of geographic information in Spain, either through its own legal mandate or as a co-producer. The ecosystem of portals associated directly with the institute consists of the IGN Download Centre, the IGN Map Library and the Online Shop of the National Centre for Geographic Information. Integrating all these sources of information was the main motivation behind the design of a new geospatial search engine.

The remains of this paper are structured as follows. Section 2 describes the state of the art on mental models for user interaction. Next, section 3 describes the proposed methodology to compare the conceptual model of the search engine and the extraction of the user mental model after the corresponding user experiments. Section 4 provides the results obtained after applying the methodology for the new geospatial search engine of IGN. Finally, section 5 provides some conclusions and future lines of research.

2 State of the art on user mental models of user interaction

"Mental models are the mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future system states" [17]. The notion of a mental model has been a widely accepted concept in the human interaction literature since the 1980s [18]. However, the challenge of measuring, representing and using mental models remains with the development of increasingly sophisticated software applications.

In the computer systems design process, it is worth distinguishing between the mental model of designers, also known as the conceptual model, and the mental model of users [3]. In the first case, the system designer has a representation of the target system and translates those ideas into a concrete implementation. While the second recognises what users actually know about the system from their cognitive abilities, previous experiences, problem-solving strategies and individual differences.

According to Nielsen [12], designers often have complex mental models of their own creations, leading them to believe that every feature is easy to understand. In contrast, mental models of the user are likely to be more limited, so they are more likely to make mistakes and find the system much more difficult to use. The common gap between the mental models of designers and the mental model of the user gives rise to a concept called the execution gulf. It is the difference between the intentions of the users and what the system allows them to do or how well the system supports those actions [13].

There are multiple conceptualisations of the types of mental models and how to represent them. De Kleer and Brown distinguish between component and causal models [4]. Component models focus on structure, while causal models explain the functioning of the system in terms of cause-effect relationships. Carroll and Olson compile four types of models: surrogates, metaphors, crystal boxes and networks [3]. Surrogate models mimic the input/output behaviour of systems. Metaphorical models directly compare the target system and some other system known to the user. Crystal box models are a hybrid between metaphors and surrogates. Finally, network models contain the states of a system and the actions that the user can take to move the system to another state.

Knowing the mental model of users has two main areas of application in the context of human-computer interaction, designing interfaces and user training [3]. The interface could be designed to reflect the predominant mental model of the users, allowing them to learn it with less guidance and perform it with fewer errors. On the other hand, a deficient mental model can be a barrier to users taking full advantage of the potential of the system. In this scenario, users can be trained and guided to learn appropriate conceptual models.

The Jakob's law is a proposition fully aligned with the idea of mental models [11]. The law states that users tend to develop expectations of design conventions based on their accumulated experience with other websites. This means that users will likely expect a website to conform to the design patterns and conventions they have encountered elsewhere, and may struggle to adapt to new or unfamiliar designs.

Three methods are commonly used for representing or describing the mental models of users [21]. The first one involves eliciting verbal accounts from participants [14], which can be done by asking them to describe a system or its mechanism, provide analogies or metaphors, or think aloud while performing search tasks. Transcripts of these accounts are then analysed to develop representations and assessments of mental models of the system being studied. The second method is drawing, where participants are asked to create a picture or diagram to represent their mental image of a system [7]. The third method involves observing errors during searches to identify gaps in their mental models of the system. When the goal is to represent mental models, the observation method is often used in combination with think-aloud protocols [16].

Over the decades of the existence of the web, numerous researchers have undertaken the difficult challenge of eliciting, measuring, and representing the behaviour of users of digital systems [1,6]. In the context of user interfaces, the concept of interaction mining stands out for its orientation to the design of applications driven by user behaviour data. Interaction mining can be defined as the capture and analysis of both static (UI layouts, visual details) and dynamic components (user flows, motion details) of the design of an application [5].

3 Methodology

The methodology applied to mine user interactions and discover their mental model consists of three phases. Firstly, the target system is dissected to identify its conceptual model and the activities to be mined. Secondly, a search task is designed and executed with representative users, while their interactions are appropriately recorded. Finally, the mined interactions are analysed to discover patterns that can be used to infer the mental model of the user.

3.1 Overview of the Geospatial Search Engine and its conceptual model

The new geospatial search engine of the Linked Cartography project gives access to two million geographic resources that were earlier dispersed across multiple platforms at the institute [2]. Figure 1 displays the user interface for the three navigation levels of the search engine: a) Quick search, b) Advanced search & results, and c) Metadata pages.

We mapped the activities that the user can perform within each level. A text search bar is the central element of the quick search page. In addition, there is a button that allows users to access advanced geographic search options. These options accept a variety of inputs, points, polygons, geometry files, coordinates and cadastral references. Thematic category filters are also available. After conducting a search on the quick search page, users are directed to the advanced search & results which is the heart of the platform. The search options available on the quick search page remain at the top of the page. The centre of the page displays a list of search results, each of which can be interacted with in various ways, such as viewing, downloading, purchasing, or locating the corresponding geographical resource. A list of faceted filters is located on the left side of the page, which allows users to refine their search results. On the right side of the page, a map is displayed that can be used to locate and visualise the results. When a result is selected, the perimeter of the corresponding resource is highlighted on the map. Users can adjust the zoom level of the map, pan around, and add a wide range of additional geographic information layers. Upon selecting a specific resource from the list of results, the user is redirected to a metadata page that provides more detailed information about the resource. This page also allows users to perform actions such as downloading, purchasing, or locating the corresponding resource.

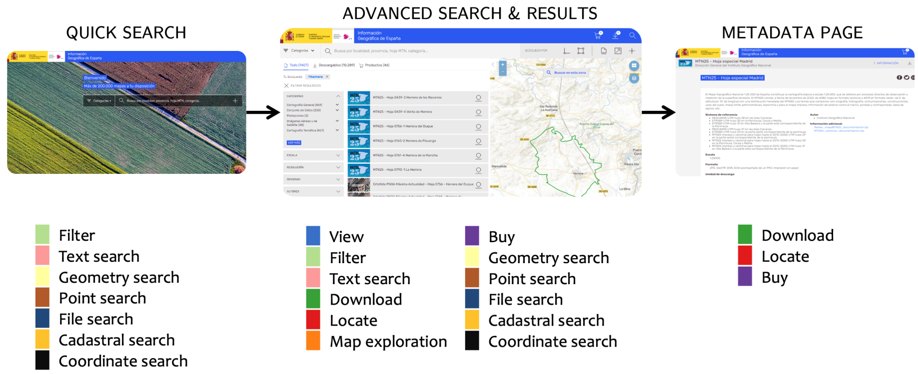

Fig. 1. Semantic search engine interface.

The conceptual model of this geospatial search engine can be understood as a mixed model that integrates a search engine and a geographic information system (See Figure 2), building upon the metaphorical notion of mental models that compare the system to archetypal systems. On the one hand, the left part is influenced by the typical search engine interface characterised by two attributes: a type-keywords-in-entry-form and view-results-in-a-vertical-list [8]. On the other hand, the right part is influenced by the typical geographic information system where the map is the dominant element -it occupies more than 90% of the area in pure GIS interfaces- [15]. However, designing such a system requires more than simply adding features from each archetype. It is crucial to enable users to explore search results with the flexibility of a search engine while also providing a comprehensive understanding of the geographic context. Therefore, integrating the two systems must be seamless and intuitive for users to have a meaningful and efficient search experience.

3.2 Experimental setup

Twenty-one participants were recruited for this study and were divided equally into three categories: I. Novice users, II. Expert unfamiliar users, and III. Expert familiar users. This division has been proposed based on the hypothesis that domain experience and familiarity with particular conventions, such as those embedded in the platforms of a specific data publisher, can have an impact on behaviour and mental models. Table 1 displays the sample distribution of each group based on their gender, age, and education. Prior to the session, all participants signed an informed consent form and completed a pre-test questionnaire to confirm their assigned category.

To comply with security restrictions, external users were unable to directly access the browser version used for testing. Therefore, the sessions were structured in a screen-sharing setting that requires participants to verbally communicate their actions to the moderator. Participants were instructed to provide

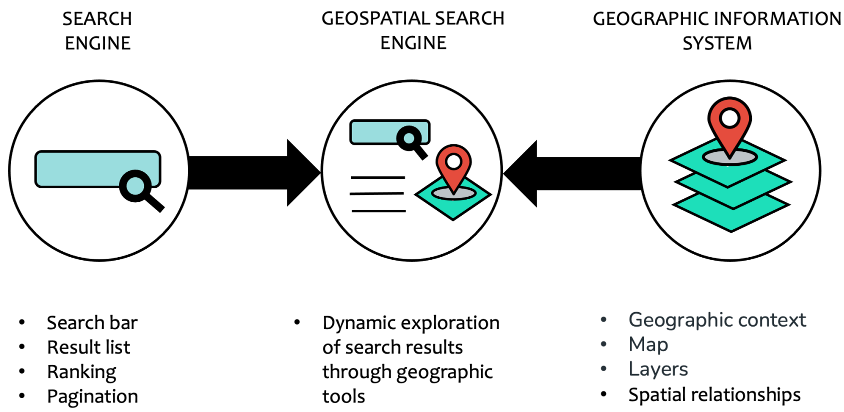

Fig. 2. Conceptual model of the geospatial search engine.

Table 1. Participant demographics, n (%).

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

detailed instructions at the lowest possible level, specifying the interface elements they wanted to interact with and how to do it. All sessions started from the quick search page.

The search task selected for the sessions represents the intended use of the geospatial search engine given the importance of tourism in the volume of queries coming into the National Geographic Institute: planning a trip to a National Park in Spain.

"This Christmas you are planning to visit the Sierra Nevada National Park and you would like to have some information about the area. You should use the search engine to look for resources that will help you get to know the area better. Identify information about the park, download files or add to the cart products that you consider most useful for the trip".

The video of the sessions was recorded and, at the same time, a web extension called Record/Replay [3] recorded the clicks made with a time stamp.

3.3 Data preprocessing and analysis

This research was designed following the principles of interaction mining [5]. Once the interactions are mined, they can be analysed using a wide variety of quantitative and qualitative methods. In this study, we opted to use a combination of exploratory visual process mining tools along with descriptive and inferential statistics to analyse the data.

Once the sessions were completed, a researcher reviewed the videos to identify the occurrence of the activities of interest. Note that it was not possible to take advantage of the click log generated during the sessions for automatic activity mapping because it was too noisy. The final result of the annotation was an event log consisting of three attributes: case (session identifier), activity, and timestamp. The event log was captured in a comma-separated value file and processed with PM4PY [4], a process mining library in Python.

For the visual inspection of interactions, dotted and variant explorer charts were used. Dotted and variant explorer charts are popular visual analytic tools that provides a helicopter view of the process [20]. In dotted charts, each event is depicted as a dot in a two-dimensional plane where the horizontal and vertical axes represent the time and class of the event respectively. Whereas a variant explorer shows all the different paths taken by a specific process in the observed cases. These visualisations were made using PMTK (a front-end solution built on top of PM4Py) [5] and Excel (for a customised adaptation of the dotted chart).

In addition, a Kruskal-Wallis test was used to compare the behaviour of different groups of users across variables such as event duration or frequency. This non-parametric method determines whether two or more samples come from the same distribution. If the result of the Kruskal-Wallis test is statistically significant, then a Dunn's post hoc test is used for pairwise comparisons between each

[3] `github.com/tomgallagher/RecordReplay`
[4] `pm4py.fit.fraunhofer.de`
[5] `pmtk.fit.fraunhofer.de`

group to identify which groups are different. The test statistic, which is a variable calculated from sample data used to determine whether the null hypothesis can be rejected, and the p-value are reported. The statistical significance level was set at .05, meaning that p-values below this threshold indicate a significant difference. These calculations were performed using Python libraries such as pandas, scipy.stats [6] and scikit_posthocs [7].

4 Results

Figure 3 shows a dotted chart where each line represents the events corresponding to a session. The horizontal axis has the duration of the session in minutes elapsed. Finally, the colour of each dot is given by the type of activity executed by the participant. To analyse the data, we first grouped the traces by participant type and then sorted them in descending order based on total session duration. We found that the sessions varied widely in both duration (median=44.1, max=20.7, min=7.7) and number and sequence of activities performed (median=16, max=30, min=6). Our analysis also revealed significant differences between user groups. Novice users had shorter session durations and performed fewer activities than the other two categories, as indicated by the graph. These differences were confirmed by the Kruskal Wallis tests (k=6.60, p=0.037 for session duration and k=6.05, p=0.049 for number of activities). A post-hoc test further showed that the novice group was the main source of the observed differences.

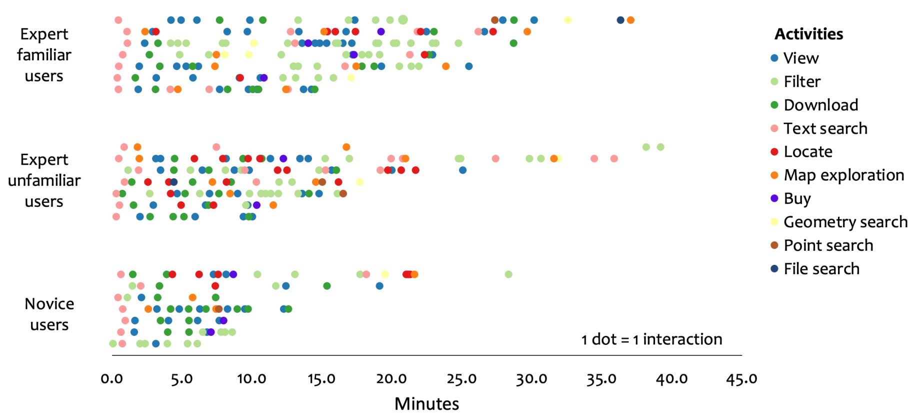

Fig. 3. Dotted chart distribution of the events over absolute time.

[6] docs.scipy.org/doc/scipy/reference/generated/scipy.stats.kruskal.html
[7] scikit-posthocs.readthedocs.io/en/stable/generated/scikit_posthocs.posthoc_dunn

Figure 4 illustrates the median number of interactions for each activity type, sorted in descending order by the median of the total. The left section of the figure shows the values broken down by activity type and participant group, with the p-values of the Kruskal-Wallis test for differences between groups displayed in the last column. The right section presents dot plots of the total number of interactions for each activity in three parallel lanes representing the three participant groups: Novice users in pink, expert unfamiliar users in light blue, and expert familiar users in dark blue. The horizontal axis in this section represents duration as a percentage of progress in the session.

The Kruskal-Wallis test did not detect significant differences between groups for any activity. When we consider the median of the total number of interactions as a reference to profile the behaviour of a representative user, we can observe that View (4) and Filter (4) are the most frequently executed activities, followed by Download (2), and finally Text search and Map exploration, which are typically executed once in the search process. Activities such as Locate, Geometry search, Point search, and File search were not executed in a typical session. The Cadastral search and Coordinate search activities were not used by any user in this sample. As expected, activities with higher frequency correspond to a higher number of points. The distribution of points suggests that there may be differences in the timing of the session where certain types of activities are more likely to be executed. We will discuss this further below.

Median number of interactions					
Activities	Novice users	Expert unfamiliar users	Expert familiar users	All	p-value
View	2	4	6	4	0.06
Filter	2	2	5	4	0.50
Download	2	3	2	2	0.55
Text search	1	2	2	1	0.09
Map exploration	0	1	1	1	0.31
Locate	0	2	0	0	0.31
Buy	0	0	1	0	0.57
Geometry search	0	0	1	0	0.20
Point search	0	0	0	0	0.75
File search	0	0	0	0	0.37

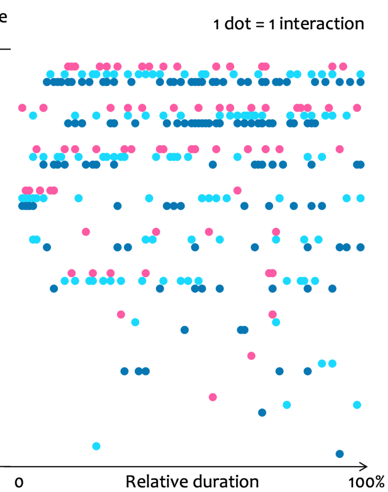

Fig. 4. Dotted chart distribution of the events over relative time.

In order to show the diversity and structure of the process flow, Figure 5 displays a variant explorer graph on the left and a relative timeline showing the expected time of occurrence for the various activities on the bottom right. The variant plot displays the considerable variability in the number and structure of activities observed across the sample of sessions, with no repeated sequences and few generalisable patterns. However, we did note that most sessions began with a textual search, sometimes followed by a filter. In the quick search page, the advanced search activities were not executed by any of the users. Additionally, several traces ended with filter sequences (light green frames), which were not always followed by resource exploration activities.

The timeline provides insight into the temporal distribution of activities across sessions and suggests that certain activities may be more prevalent at certain stages of the search process. Text search tended to occur at the beginning of the session and was the earliest activity performed. This was followed by View and Download, which typically occurred near the end of the first half of the session. Map exploration, Filter, and the remaining activities tended to occur somewhat later, after the middle of the session.

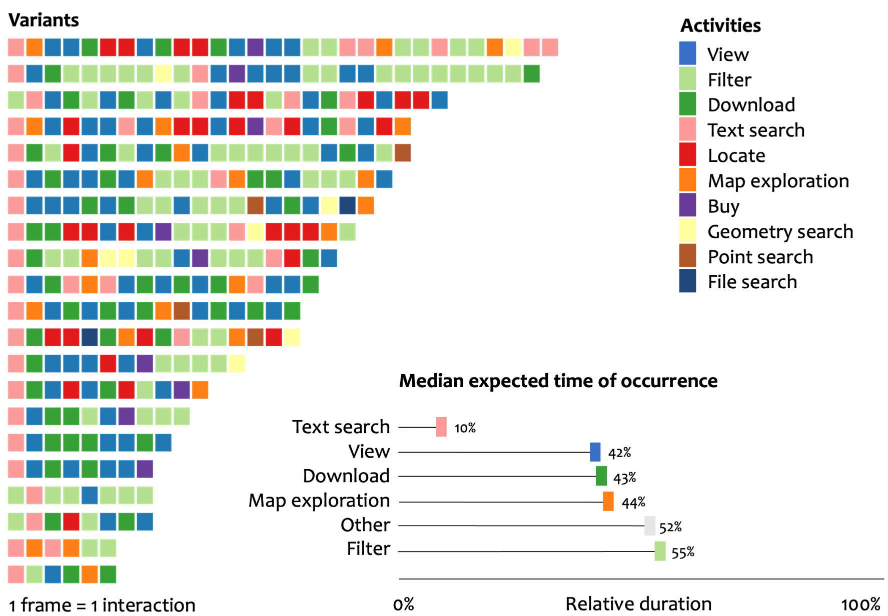

Fig. 5. Variants explorer sequence of events.

5 Conclusions

In this paper, we explored how interaction mining techniques can be applied to discover mental models of the user in the process of designing a geospatial search engine. These mental models can help to adjust the behaviour of the system to meet the expectations of users and to educate the user about functionalities that are currently unfamiliar. A new geospatial search engine, developed by the Spanish National Geographic Institute, was used as a starting point to develop a case study. During this case study, representative users were recruited to conduct usability tests of the new portal. The sessions were recorded, processed, transformed into event logs, and analysed using process mining techniques along with descriptive and inferential statistics. The results suggest that the observed mental model prioritises the features of an archetypal search engine over those of a geographic information system. This behaviour deviates from the mixed model of the creators of the system.

The analysis yielded several insights for the platform development team. The first relevant finding was the clear distinction between the frequently used functions and the infrequently used ones in an ordinary search. A Pareto dynamic [19], where a limited number of functions are responsible for most interactions, has implications for UX design. Identifying hot spots can help the team narrow their focus, optimise scarce resources, and increase impact. This does not mean that the features that are used less frequently should be discarded, but rather carefully studied for their contribution to the user experience. This is the case for all geographic features that had a marginal interaction frequency with respect to simpler search and explore activities or were relegated to a late phase of the session after trying the simpler search strategies. For example, despite being a tool that can significantly contribute to the exploration of geographic resources and cover a considerable area of the interface, the map received less attention than expected by the product team. This has led designers to rethink the role and presentation that the map should play in the overall search experience. The same applies to other underused functions such as file, cadastral or coordinate search that could be dropped from the initial design.

Modeling user behaviour during usability tests also proved to be a mechanism for detecting quality problems in the system. By observing users when interacting with filters, the design team was able to identify functional problems in the portal. Reviewing session videos revealed that the filtering threads were a user response to malfunctions in the filtering mechanism.

The experiment had several limitations that need to be considered. While the number of participants was appropriate for usability testing, where the aim is to capture an overall understanding of user behaviour, it may be limited for drawing quantitatively sound conclusions. This limitation is particularly relevant for detecting differences between novice and expert groups, which may require a larger sample size to achieve reliable results. Additionally, the use of a think-aloud design mediated by a moderator could be viewed as a potential contaminating factor. The presence of a moderator may have influenced the behaviour of participants, resulting in longer execution times and more complex operations than they would normally perform -particularly for specialised users-. The interference of the moderator may also have prevented the observation of errors that the participants would have made in a hands-free exercise. Despite these potential drawbacks, the think-aloud method proved useful for the researcher in understanding the reasoning behind the behaviour of participants. This information would later be used for modeling and interpreting the observed behaviour. By concentrating on observing the interface and verbalising what they want, users reveal the imprint of what they see or do not see of the system.

This study has identified several lines of future work. Firstly, although the current implementation of an automatic event logging tool did not achieve the intended support for event log annotation, there is still significant potential to automatically model the behaviour of web systems operating under considerable traffic. A major challenge is to accurately map user clicks and keystrokes to activities that are meaningful from a process and business perspective. Secondly, the intervention of a moderator prevented executing a fine-grained analysis of performance, but such an analysis would be valuable in the case of task mining traffic from a portal in operation. Thirdly, other typologies, such as network models (graphs), can also be explored for describing the mental model. Process mining techniques related to flow control can greatly contribute to this purpose. Fourthly, this work only addressed the gap between the conceptual model and the mental model of the user from a process discovery perspective, but there is also an opportunity to deepen this understanding from a conformance verification perspective. This branch of process mining diagnoses the differences between a prescriptive model and the behaviour captured in the event log. Finally, personalised and real-time support mechanisms can be developed to enhance the experience of users with deficient mental models based on their usage patterns of the platform, as proposed by Jansen (2020) under the concept of adaptive UIs for users of geoportals [9].

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