Revisiting Interest Indicators Derived from Web Reading Behavior for Implicit User Modeling

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ABSTRACT

Today, intelligent user interfaces on the web often come in form of recommendation services tailoring content to individual users. Recommendation of web content such as news articles often requires a certain amount of explicit ratings to allow for satisfactory results, i.e., the selection of content actually relevant for the user. Yet, the collection of such explicit ratings is time-consuming and dependent on users' willingness to provide the required information on a regular basis. Thus, using implicit interest indicators can be a helpful complementation to relying on explicitly entered information only. Analysis of reading behavior on the web can be the basis for the derivation of such implicit indicators. Previous work has already identified several indicators and discussed how they can be used as a basis for user models. However, most earlier work is either of conceptual nature and does not involve studies to prove the suggested concepts or relies on meanwhile potentially outdated technology. All earlier discussions of the topic further have in common that they do not yet consider mobile contexts. This paper builds upon earlier work, however providing a major update regarding technology and web reading context, distinguishing between desktop and mobile settings. This update also allowed us to identify a set of new indicators that so far have not yet been discussed. This paper describes (i) our technical work, a framework for analyzing user interactions with the browser relying on latest web technologies, (ii) the implicit interest indicators we either revisited or newly identified, and (iii) the results of an online study on web reading behavior as a basis for derivation of interest we conducted with 96 participants.

CCS CONCEPTS

• Information systems \rightarrow Personalization; Web log analysis; Recommender systems; • Human-centered computing \rightarrow Empirical studies in HCI;

KEYWORDS

web reading behavior, user modeling, implicit interest indicators

1 INTRODUCTION

As in the previous years the web was constantly growing, it gets more and more important to understand users to be able to present Johannes Schönböck University of Applied Sciences Upper Austria Department of Communication and Knowledge Media Hagenberg, Austria johannes.schoenboeck@fh-hagenberg.at

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relevant information to them. In order to implement more intelligent websites, different kinds of interest indicators can be helpful when predicting user interest in certain web content elements, e.g., news articles. In general, user interests can be gathered in (i) an explicit manner [12], i.e., asking questions to users, (ii) an implicit manner [11], i.e., information is gathered by a user's behavior or in (iii) a hybrid manner, i.e., a combination of implicit and explicit means. Both, explicit and implicit ratings or indicators can provide a good foundation for recommendation of other, previously unseen web content elements. However, implicit means relieve the user of the burden of rating every content on its interestingness [26]. Concerning gathering user interests on the web, one may further distinguish between (i) server-side and (ii) client-side profiling [1]. While server-side approaches basically rely on analyzing HTTP requests, client-side approaches allow for continuous monitoring and a more profound analysis of user interaction [7].

Therefore, this paper focuses on a *client-side* analysis of *implicit interest indicators* derived from web reading behavior. It builds upon earlier work (see e.g., [2, 9, 26, 27]), revisiting known indicators with state of the art web technologies. During this process, we could additionally identify novel indicators that have not been discussed so far. Further, our work contributes new insights as it explicitly distinguishes between desktop and mobile contexts which has not been the case in earlier research.

The paper further presents the results of a study conducted with 96 web users. The study aimed at determining the informativeness and suitability of particular implicit interest indicators (i) for web users in general and (ii) for individual web users in particular. We provide insights into the indicators themselves (e.g., their potential to reliably predict user interest), how they may be obtained by JavaScript (JS) and additionally suggest a possible base structure for user models relying on reading behavior. This structure can be considered as a foundation for subsequent work. Further, we envision the results of our study as a basis for later recommendation of content in intelligent web user interfaces.

2 RELATED WORK

This section describes related work on (i) technologies underlying client-side analysis of implicit interest indicators, (ii) the indicators themselves, and (iii) user studies related to implicit interest analysis.

Technologies. Early approaches were based on custom browsers [2, 23] or browser plugins [6]. Whereas these approaches do not suffer from any limitations of web browsers, the application thereof is hindered since the user needs to install additional software. In contrast, more recent approaches base on JS and AJaX, which is commonly supported in today's web browsers and allows sending data to a web server for persisting it in a user profile. A vision of such systems is presented in e.g., [7, 8, 27]. However, none of the earlier approaches explicitly mentioned the inclusion of mobile browsers on tablets or smart-phones although nowadays more and more users use the "mobile web". Thus, our approach puts special emphasis on including mobile browsers and how to obtain interest indicators during surfing on mobile devices (cf. Section 3 and 4).

Implicit interest indicators. A first high level categorization of implicit interest indicators distinguishing between *marking* (e.g., bookmarking), *manipulation* (e.g., cutting and pasting or searching), *navigation* (e.g., following a link), *external* (e.g., a user's heart rate or temperature) and *repetition indicators* (e.g., spending *more* time on a page or doing *lots* of scrolling) is presented in [2].

First approaches to derive implicit indicators focused on the whole web page as a single source of information resulting in rather coarse-grained indicators. In [10], fragmentation mechanisms (e.g., *split by vertical position, split by content type* or *split by structural information*) were proposed to allow for a more fine-grained analysis. This led to new interest indicators as well, i.e., *visible time, mouse over time, mouse on same y time, number of mouse moves, number of clicks* and *number of text selections*. Based on these considerations, an algorithm to predict which paragraphs in a HTML document have been read, was presented [9].

In [21], special emphasis was put on indicators derived from mouse movements. There, a classification scheme for mouse movements distinguishing between *decision-only* (i.e., mouse movement related to an explicit rating such as moving the mouse to a "relevant" button), *horizontal*, *vertical*, *highlighting*, *re-scoping* (i.e., a movement related to changing the mouse position after loading a new page), *scrolling*, *random*, and *no-movement* was proposed.

In [26], another categorization of implicit interest indicators that, on the top level, involves *time* (active and passive), *mouse* (clicking, scrolling and movements) and *keyboard* (movements via cursor keys and shortcuts) was discussed. This categorization builds the primary basis for our approach described in this paper. The same authors stated in [27] that a relative ordering and a combination of implicit indicators may further improve relevancy.

Although a lot of valuable research has been conducted on implicit interest indicators, to the best of our knowledge, mobile devices and indicators thereon have not been considered up to now. Consequently, in this paper we discuss to which respect indicators analyzed for desktop usage may be applied also on mobile devices and which new indicators result from mobile devices.

User Studies. A first user study with 72 students on analyzing the correlation between implicit and explicit interest indications was conducted in [2]. Yet, this study merely focused on time-based

indicators (i.e., *time spent on a page, time spent moving the mouse, number of mouse clicks,* and *time spent scrolling*). The results suggest that *time spent on a page* and *time spent scrolling* are good indicators of interest. Regarding *time spent moving the mouse,* a positive relationship between the indicator and the explicit rating could be found but it is expressive mainly for determining which pages have the least amount of interest. For distinguishing between higher interest levels, the indicator is not accurate. For *number of mouse clicks,* no correlation with the explicit rating could be found.

Reading behavior as basis for the derivation of user interest was further analyzed in [7-10]. In [10], a study with 53 users comparing the results of client-side user monitoring and explicit user feedback is presented. A single page containing news items was used for the study and the following indicators related to mouse activity were used to determine whether an item has been read: mouse time above item, mouse time on same y as item, time item is visible, amount of mouse moves above item, number of clicks on item, and number of text selections in item. The results suggest that generally, the observation of client-side activity at least doubles the probability that an item has been read (80% of the items with no activity had not been read). Yet, the authors also found that about half of the items with interaction times or mouse movements have been skipped as well [10]. Regarding the individual indicators, the study revealed a positive correlation between mouse over time and a higher probability the item has been read. Further, mouse moves, click events and text selection have been shown to be strong indicators while visibility time and vertical mouse position did not allow for sufficient conclusions. The study design in [10] is similar to ours, however, we did not mainly aim at predicting whether an item has been read or not, but how interesting it was (as a basis for future recommendation). Further, we integrated more indicators (including such relevant for a mobile context).

In [9], an eyetracking study was conducted in order to determine whether content elements have been read or not. Eyetracking in this case provides a more reliable explicit source of information, compared to users' statements. The study e.g., revealed that prediction of a user's gaze position is more accurate while the mouse is in motion and that mouse actions (such as text selections, clicking or mouse movements) allow for better predictions but these activities occur only for a fraction of the total observation time. Related to this, in our study, we observed that user behavior related to mouse activity is highly individual (thus, the related indicators perform well for some users but fail for others).

More recently, a study with 50 participants, analyzing implicit interest indicators based on *mouse* (i.e., *movement*, *click* and *scroll*) and *keyboard* (i.e.,*shortcuts* and *movements*) activities was conducted [27]. The indicators were analyzed by collecting the users' explicit statements since the users were asked to rate their behavior regarding mouse or keyboard activities. E.g., users had to rank different mouse actions (movement, click or scroll) based on their frequency of usage. This approach might be error-prone as it is dependent on users' realistic answers. We thus rely on automated analysis of user activities on a web page only.

In [21], an analysis on data of an earlier study [22] with 48 participants that had to judge the relevance of news documents and document summaries was conducted. Additionally, different kinds of mouse movements (*decision only, horizontal, vertical, highlighting*,

re-scoping, *scrolling*, *random* and *no-movement*) were captured as implicit indicators. While the classification of mouse movements is interesting, we believe the results might be biased by the way how users had to rate the relevance of the documents, i.e., through clicking a "relevant" or "not relevant" button on top of the page. Most users thus moved only between these buttons which is why more general conclusions based on mouse activity inside the actual text area are not possible. We thus separated the reading area from the area to provide explicit feedback in our study.

3 IMPLICIT INTEREST INDICATORS

In the following, we present implicit interest indicators that we considered in our implementation (cf. Section 4) as well as in our user study (cf. Section 5), mainly based on the indicators suggested in [9, 27]. We categorize the indicators by their source of origin as well as their support on desktop or touch-based mobile devices (cf. Table 1). After describing the general intention, we briefly outline how the indicators may be detected by means of recent JS technology (including plain JS as well as frameworks).

3.1 Time-Based Indicators

Time-based indicators try to derive user interests by means of the time spent on a website or visibility time of a fragment. By a fragment we mean a specific part of a website, e.g., a paragraph or a div-container, which can be defined by a programmer by assigning an explicit class (cf. Section 4 for details). In general it has been proven that the more time a user spends on a website the more interesting it is to him/her [2, 4, 15, 19, 25, 26]. The time spent on a website may be split into *active* and *passive* intervals. Active interval means the duration a user is reading a text or interacting with the website whereas passive interval means the time where the website is shown in the browser but there is no user interaction (it is assumed that the user is distracted from the website during this period of time). In JS, the elapsed time between two events

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Table	1:	Overview	ot	imp	licit	indicators

	Indicator	Desktop	Mobile
Time	Visibility	1	1
	Random Movement	1	×
	Move in Fragment	1	×
M	Mouse over Fragment	1	×
Movement	Horizontal Movement	1	×
	Vertical Movement	1	X
	Mouse on Same Y	\checkmark	×
Contact	Contact in Fragment	1	1
	Contact on Same Y	×	1
T	Select	1	1
Text	Cut & Copy	\checkmark	1
	Zoom	1	1
Other	Swipe	×	1
	Orientation Change	×	1

is compared. If it exceeds a certain delta (60 sec. by default) it is considered as a passive, otherwise as an active interval.

Visibility. This indicator determines how often and how long (cf. *Visibility Count* and *Visibility Seconds* in Section 5.4) a fragment of a website has been visible, i.e., it has been within the viewport of a user. This is especially relevant for handling vertical and horizontal scrolling irrespective of the source of origin, i.e., it does not matter if scrolling is indicated by the mouse wheel, a page down button press, by using the scrollbar or by swiping on mobile phones. Furthermore, we do not solely count the number of scroll actions as done e.g., in [2], but focus on the actual visibility time of a fragment in order to derive if the text has been read or not depending on the length and difficulty of a text within a fragment [10].

Every time the visible part of a website changes, the scroll event is thrown in JS, both on desktop and mobile devices. Within the according event handler for every fragment of a web page its size and its relative position to the viewport are calculated which is than compared with the current viewport of the browser window to calculate the active visibility time of a certain fragment using the timestamps of the scroll event. The combination of time spent and scrolling has been shown as a valuable indicator in [16].

3.2 Movement-Based Indicators

Indicators that stem from mouse movements are subsumed under *movement-based indicators*. Since there is no mouse pointer on mobile devices, these indicators apply to desktop devices only.

Random Movement and Move in Fragment. It is assumed that the more frequent mouse movements within a fragment are, the more likely the user is also looking at a certain fragment [17, 24]. Yet, mouse movements might not be a very good indicator that a certain fragment is of interest, but no movements strongly indicate that it has been skipped and is thus not interesting to the user [21].

Mouse over Fragment. Studies revealed that users tend to place the mouse within a text they are currently reading [9, 21]. This indicator measures how often and how long (cf. *Mouse over Fragment Count* and *Mouse over Fragment Seconds* in Section 5.4) the mouse is placed over a certain fragment to derive the interest depending on the length and difficulty of the text.

Horizontal Movement. Horizontal movements of a mouse, if happening regularly and over several lines of a text, might indicate that a user uses the mouse as a "pointer" for reading [21].

Vertical Movement. Similar to horizontal movements, vertical movements of a mouse might indicate that users use the mouse to "mark" the current line of text that they are reading [21].

Mouse on Same Y. Whereas the last two indicators assume that a user is moving the mouse along the text when reading, this indicator relates to users that place the mouse e.g., on the right side of a website, when starting to read but do not move the mouse during reading. Those fragments that are on the same horizontal line, i.e., y-coordinate, are assumed to be of interest [10].

Detection in JS. To detect *movement-based indicators* the mouse events of JS need to be handled. In particular, the mousemove event can be used to track all movements of the mouse. For *fragment-based indicators* the mouseenter and mouseleave events may be used in order to count how often and how long a fragment has been visited. Horizontal and vertical movements may be detected

by comparing the pageX and pageY attributes of the mouse events. However, since users are not able to move the mouse in a straight horizontal/vertical direction some fuzziness needs to be respected. For the indicator *Mouse on Same Y* additionally the scroll event is considered to check for new fragments after scrolling.

3.3 Contact-Based Indicators

These indicators relate to click (desktop) and touch (mobile) activity. The latter is a novel addition to earlier collections of implicit interest indicators and has not been analyzed before.

Contact in Fragment. This indicator recognizes a click (irrespective of right/left mouse clicks on desktop or touch/press on mobile devices) in a certain fragment. Especially if a link is clicked one may conclude that a fragment is of interest to a user [4, 20, 25].

Contact on Same Y. Similar to placing a mouse near the text of interest, we assume that a user might use a touch interaction to "mark" the fragments on the same horizontal line for reading.

Detection in JS. A click can be recognized by attaching click event handlers (desktop devices). For mobile devices (tap and press (long tap) handlers) we utilized the external library hammer.js¹.

3.4 Text-Based Indicators

Select, Cut and Copy. Although the selection and copying of a text occurs relatively seldom compared to the other indicators, studies found out that a selected text indicates high relevancy [10, 11, 26]. The mouseup event on desktop and the touchend event on mobile devices may be caught. Additionally, it needs to be checked if the according event object contains a so called selection object which contains the selected text. Furthermore, on desktop also the keyup event needs to be registered in order to check for text selection via the keyboard (e.g., by Shift + cursor keys). If a text is cut² or copied, JS provides the cut and copy events which also contain this text.

3.5 Other Indicators

Here we describe further indicators rather specific for the mobile context. All of them are novel contributions to work on implicit interest indicators and have not been analyzed in this context before.

Zoom. If a user is interested in a certain fragment, he/she might try to enlarge this fragment. Although zooming is not commonly used on desktop, we assume it is especially important on mobile devices. To detect a zoom on mobile devices, we again utilize hammer.js which provides a pinch event. Besides the information from the event itself, it is also necessary to detect the fragments that are visible after zooming, which is done as described for *visibility*.

Swipe. Swipe means a fast scrolling on mobile devices. We assume that fragments that have been skipped during swiping might be of no interest since the user can not see them. This is why we explicitly considered swiping in contrast to scrolling which allows at least some skimming of a text. Still, scrolling is part of several other indicators. To detect this indicator we use jQuery Mobile³ which provides scrollstart/scrollend as well as a swipe event. When starting (scrollstart) or stopping (scrollend) a swipe, the

visible fragments are temporarily saved in two separate lists. All fragments during a swipe are saved in an extra list which is then used to build the intersection with the lists of visible fragments at the beginning/ending of the swipe to obtain the skipped fragments.

Orientation Change. Mobile users sometimes turn their mobile phones from portrait to landscape view if they are reading a certain fragment and back to portrait if they are finished. Again, in combination with others, this indicator might increase certainty that a fragment is of interest to a user. Modern browsers support the JS event orientationchange, otherwise jQuery Mobile provides a workaround. Besides the data from the event, it is also necessary to check for the visible fragments after the orientation changed.

4 IMPLEMENTATION

This section presents the general architecture of our current prototype (cf. Figure 1) as another contribution of the paper. The prototype may roughly be divided into a client-side *Implicit Indicator Library* component and a *REST API* as well as the *database* on the server side as described in the following.



Figure 1: Overview on Prototype Architecture

4.1 Implicit Indicator Library

The core component of our prototype is a JS library to obtain the indicators described above (cf. *Implicit Indicator Detection API* in Figure 1). To apply the library to an HTML document – in our user study a Typo3-based news site – the programmer needs to assign a unique CSS class (configurable via the library settings) to the HTML elements that should be handled as a fragment. During initialization, the fragments of the HTML documents are automatically obtained, whereby we respect the hierarchical ordering of the DOM tree, e.g., if an indicator is detected on a child fragment it is also propagated to its parent fragments. However, if solely the actual fragment where the indicator occurred should be tracked, this may again be configured in the library settings. Further, the library may be configured based on which indicators are of interest for the programmer, i.e., it is possible to enable/disable tracking of

¹https://hammerjs.github.io/

 $^{^2\}mathrm{On}$ a website it is not possible to actually "cut" a text, thus the event is treated as equal to copy.

³https://jquerymobile.com/

indicators. To minimize REST calls to the server (cf. Section 4.2) and to omit a loss of data in case that internet connection is lost or the server is offline, the Web Storage API⁴ is used to provide an intermediate data store on the client. Thus, not every event or implicit indicator is immediately pushed to the server but only after a certain time span (30 sec. by default) or the maximum number of local events/indicators occurred (50 by default).

4.2 **REST API and Database**

To persist the data of the detected events and indicators in a database on a server, we make use of the REST protocol. On the client side, we provide functions which wrap the data of the events/indicators into according JSON objects which are then used by respective POST methods to submit the data to the server (cf. Indicator REST API in Figure 1). On the server side, the according REST API is defined using the Laravel⁵ framework. Besides methods that store the events and indicators in the underlying MySOL database also means for authentication are provided to assign the occurring events or indicators to users. Figure 2 shows an extract of the database in terms of an UML diagram. A User is connected to Sessions, which represent a certain interaction with a website via a specific browser. Furthermore, the actual Webpage and its Fragments are stored in the database. In case a user interacts with a web page, the emerging Events and/or Indicators are stored in the database and linked to the according Fragment instance. For Indicators as well as Events according sub-classes exist. However, for reasons of brevity we omitted all the concrete sub-classes and simplified the relations between Indicators and Events (e.g., to a MoveInFragement indicator only MouseMove events may be assigned).



Figure 2: Extract of Database as UML Diagram

5 USER STUDY

Here we describe the user study conducted to evaluate the indicators (cf. Section 3) and their potential for predicting user interest in web content.

5.1 Setting

The study was online for three weeks (end of September to mid of October 2018). We set up a responsive Typo3-based news page to track the indicators with the JS library presented in Section 4. The website was fully text-based to prevent additional effects stemming from the nature of pictures or other visual kind of information presentation. It contained a mix of teaser texts linked to the full-text page of 20 news articles related to different topics (sports, health, lifestyle, technology, and travelling). The articles were all similar regarding length and readability. For the latter, we used Flesch's reading ease test [5] and selected articles with similar readability scores. On a scale between 0 and 100, values between 100 and 70 are considered easy (in three gradations: very easy, easy and fairly easy), values between 69 and 60 are considered standard and values between 59 and 0 are considered *difficult* (again in three gradations: fairly difficult, difficult and very confusing). For the selection of our news articles we avoided texts that can be considered very confusing. All selected texts had readability scores between 80.4 and 42.0 (M = 63.77, SD = 10.92). The teaser texts had readability scores between 75.3 and 46.1 (M = 60.46, SD = 8.33). Of the 20 articles, 17 were in a "moderate" area with values between 79 and 50. This way we aimed at preventing a significant bias due to text complexity. Further, we selected articles that are nearly timeless (so they would not date out during the study's online time).

5.2 Procedure and Methodology

After general instructions and information on the study (e.g., related to privacy issues and data processing) the participants had to scan the overview page and take as much time as they needed to read as many articles as they liked in further detail as we wanted to be able to record as-natural-as-possible reading behavior. Since we automatically derived information about the device from the browser used, participants could freely chose the device (desktop or a mobile). After the participants finished reading, they answered a web-based questionnaire which we set up using the Unipark⁶ survey tool. The questionnaire contained (i) questions related to demographic information (age, gender), (ii) questions regarding general news reading behavior, (iii) information related to usage of devices like smart phones and desktops, and (iv) questions related to the articles themselves (whether they had noticed the individual articles and if yes, how interesting they found them on a sevenpoint Likert scale). Participation took about 20 minutes on average (about 15 minutes for reading and about five for the survey).

Before the actual user study, we conducted a thorough multiphase pretest with five selected users that did not participate in the study later. The aims of the pretest were twofold. First, the pretest allowed us to observe different kinds of user behavior during browsing our news page and reading. It helped us to identify types of actions that might happen and what meaning these actions might have for the users. For instance, one of our pretest users only

⁴https://developer.mozilla.org/de/docs/Web/API/Web_Storage_API ⁵https://laravel.com/

⁶https://www.unipark.com/

interacted with the web page when necessary (e.g., to scroll down after the bottom of the page had been reached) while another user continuously scrolled the text to keep it in approximately the middle of the screen. Other users often moved the mouse to the position of the text they were currently reading. Second, the pretest helped us to gain first insights about the indicators themselves. Third, we were able to (i) test the technical infrastructure in a study setting, (ii) ensure users understand instructions, tasks and questions without further assistance, and (iii) gain feedback related to the design of the website used for the study. During the first phase, two users underwent the full study procedure on a desktop device including a Tobii T40 Eyetracker. After this phase we changed (i) page layout, (ii) login process⁷, (iii) design of the questionnaire, and (iv) in one case, selection of news articles. The second phase included (i) another test with an additional user on the eyetracking device and (ii) two tests with a user of the first phase to validate the introduced changes. After finalizing the desktop version of the study we did a pretest on smart phones with two more users resulting in a revision of the questionnaire's layout for mobile devices.

5.3 Participants

We recruited 109 users via mailing lists of the authors' university as well as mailing lists of the user modeling research community. These users had activity on the news page and logged in to the questionnaire. Of these, 96 finished the questionnaire (the remaining 13 had to be excluded due to missing data). Participation was fully anonymous, users who wanted to have a chance of winning one of 20 Amazon vouchers, voluntarily provided their email address at the end of the study (which was not linked to the rest of their

⁷Users needed to register (solely username, no password) in order to link the reading behavior with the externally hosted questionnaire.

Table 2: Correlation (Pearson's *r*) overview for all indicators in the desktop setting. * or ** denote statistical significance (on the .05 or .001 level).

Indicator	r Overview Page	p Overview Page	r Detail Page	p Detail Page
Visibility				
Count	.032	.179	.373	< .001**
Seconds	.086	< .05*	.116	< .001**
Random Movement	.173	< .001**	.199	< .001**
Move in Fragment	.172	< .001**	.120	< .001**
Mouse over Fragment				
Count	.180	< .001**	.088	< .05*
Seconds	.203	< .001**	.220	< .001**
Horizontal Movement	.131	< .001**	.090	< .05*
Vertical Movement	.092	< .05*	.198	< .001**
Mouse on Same Y				
Count	.023	.251	.061	< .05*
Seconds	.294	< .001**	.121	< .001**
Contact in Fragment	.208	< .001**	.150	< .001**

data). Of all 96 participants, 35 were female, 61 male. 74 participants (23 female, 51 male) used a desktop device, 22 (12 female, 10 male) a smart phone. They were between 18 and 65 years old (M = 28.85, SD = 10.11). Split up into participants with desktop and mobile devices, desktop participants were between 19 and 65 years old (M = 29.82, SD = 10.86), mobile participants were between 18 and 38 years old (M = 25.59, SD = 6.13). Asked for their laptop/PC usage habits, 68 participants (70.8%) use such devices more than five hours a day, eight (8.3%) between four and five hours, six (6.3%) between three and four hours, eight (8.3%) between two and three hours, three (3.1%) between one and two hours and the remaining three (3.1%) less than one hour a day. Further, eleven of 76 participants (11.5%) use a smart phone more than five hours a day, eleven (11.5%) use it between four and five hours, 20 (20.8%) between three and four hours, 20 (20.8%) between two and three hours, 23 (24%) between one and two hours and eleven (11.5%) less than one hour. Concerning news reading behavior, eleven participants (11.5%) stated to read news several times a day, seven (7.3%) daily, 22 (22.9%) several times a week, 27 (28.1%) once a week, and 29 (30.2%) rarely or never.

5.4 Results

In this section we analyze the results of our study, split up into insights for desktop (cf. Section 5.4.1) and mobile (cf. Section 5.4.2) environments. The results are based on a correlation analysis using Pearson's r^8 between the implicit interest indicators and the users' explicit interest indication per article provided in the questionnaire. Please note that due to the moderate number of participants (especially as split up into desktop and mobile users), the identified correlations are considered as first insights to show an overall tendency. In order to gain a stable understanding, further analyses are necessary (see Section 7). Correlations were first analyzed per article per indicator per user and then summarized to identify indicators that are specifically relevant for a larger number of users. However, we argue that the significance of certain indicators and their capability to predict user interest is highly individual and might thus differ from user to user. Thus, we utilize our results to suggest a first generalizable formula which can then be individually weighed in order to form individual user models (cf. Section 6).

5.4.1 Reading Behavior on Desktop Devices. For the desktop setting, we analyzed 14 indicators in total whereby Select, Cut & Copy and Zoom had no occurrences for any of the 74 desktop users and were thus excluded. The results of the correlation analysis for the remaining 11 indicators, summarized for all desktop users, distinguishing between the news overview page and the article detail pages are shown in Table 2. This distinction is necessary because some indicators are arguably more meaningful for analysis of reading behavior on the overview or detail page (e.g., Mouse on Same Y is probably more conclusive for the overview page where there are several different fragments). We report Pearson's r as well as the related statistical significance (p). Statistically significant correlations are marked with * (.05 level) or ** (.001 level). As Table 2 shows, we mostly found (at least slightly) positive correlations. The correlation values themselves seem relatively low (even for

⁸Our data complies with the prerequisites for computation of Pearson correlation.

Table 3: Statistically significant correlations of interest indicators with explicit user interest assessment. All values except mean correlation (values between -1 and 1) are in absolute numbers (out of 74 desktop users), measured for the news overview page and detail page. Not statistically significant correlations are not included.

Indicator	Ø Correlation		# Significant		Corr. < .2		Corr. < .4		Corr. < .6		Corr. < .8		Corr. >= .8	
	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail
Visibility Count	.65	.70	13	35	0	0	0	0	3	10	8	12	2	13
Visibility Seconds	.60	.69	7	34	0	0	0	0	3	12	3	13	1	9
Random Movement	.59	.68	17	34	0	0	0	0	9	12	8	13	0	9
Move in Fragment	.60	.68	26	38	0	0	1	0	13	12	10	19	2	7
Mouse Over Fragment Count	.58	.71	15	34	0	0	0	0	9	8	6	15	0	11
Mouse Over Fragment Seconds	.61	66	19	28	0	0	0	0	10	10	6	12	3	6
Horizontal Movement	.54	.63	11	19	0	0	0	0	9	9	2	8	0	2
Vertical Movement	.50	.65	4	16	0	0	0	0	3	6	1	9	0	1
Mouse on Same Y Count	.55	.70	12	40	0	0	2	0	6	10	4	17	0	13
Mouse on Same Y Seconds	.59	.69	18	38	0	0	0	0	14	15	2	15	2	8
Contact in Fragment	.73	.64	17	15	0	0	0	0	4	7	6	5	7	3

the correlations that were found to be statistically significant). This however is only the case for the average over all users. The analysis on the level of the individual user reports a different view.

Thus, we next analyzed the results on the level of the individual (see Table 3). The table reports only the results for users where we found significant correlations between the respective implicit indicator and the related explicit answer the user gave in the questionnaire. For instance, Table 3 shows that for the overview page, the indicator *Contact in Fragment* was relevant for 17 of the 74 desktop users. For these 17 users, the mean correlation was .73 (thus, a relatively strong positive correlation). Further, the table shows that for 7 of these 17 users, the correlation was above or equal to .8, for 6 users it was between .6 and .8 and for 4 users it was

Table 4: Correlation (Pearson's *r*) overview for all indicators in the mobile setting. * or ** denote statistical significance (on the .05 or .001 level).

Indicator	r Overview Page	p Overview Page	r Detail Page	p Detail Page
Visibility				
Count	.204	< .05*	.431	< .001**
Second	.115	.073	.387	< .001**
Contact in Fragment	.298	< .001**	.304	< .001**
Contact on	.225	< .05*	.304	< .001**
Same Y Count				
Visible Before Swipe	.115	.073	.247	< .001**
Visible After Swipe	098	.108	.247	< .001**
Skipped While Swipe	.059	.227	•	
Orientation Change	•		.155	< .05*
Landscape				
Orientation Change	•	•	.155	< .05*
Portrait				

between .4 and .6. As the table shows, the indicators relevant for most users were *Move in Fragment* (significant correlation for 26 of 74 users), *Mouse Over Fragment Seconds* (significant correlation for 19 users), *Mouse on Same Y Seconds* (18 users) and *Contact in Fragment* and *Random Movement* (both 17 users).

For the news detail pages more indicators were significant for a larger number of users, e.g., *Mouse on Same Y Count* was significant for more than half of the users (40 of 74), *Move in Fragment* as well as *Mouse on Same Y Seconds* were significant for 38 of 74 users. For the detail pages, all correlations were equal to or above .4.

5.4.2 Reading Behavior on Mobile Devices. From the 12 mobile indicators in total we did not find any occurrences of Select, Cut & Copy and Zoom for any of the 22 mobile users. Thus, Table 4 shows the remaining 9 indicators for the mobile setting, again split up into correlations (and related statistical significance) for the overview and the detail pages. With one exception (indicator Visible After Swipe), we only found positive correlations. For two indicators, there were only occurrences for the news detail pages (Orientation Change Landscape and Orientation Change Portrait).

Similar to the desktop setting, we also analyzed the results on the level of the individual user, cf. Table 5. This table shows the results only for users where we found significant correlations between the implicit indicators and the users' explicit statements. For instance, the indicator *Visibility* time in seconds was relevant for 5 of 22 users for the overview page. For 2 of these 5 users, we found a correlation greater than or equal to .8, for the remaining 3 the correlation was between .6 and .8. For *Orientation Change Landscape* we did not find any significant correlations on the overview page.

For the news detail pages, we did not find any significant correlations for some of the other indicators: *Visibility Count, Visibility Seconds, Contact on Same Y* (although there were occurrences of the related events). For instance, we found significant correlations for 8 of the 22 mobile users between the indicators *Orientation Change Landscape* and *Visible After Swipe* and the related explicit interest statements. Again, the correlations for the users where correlations between indicators and explicit statements were statistically significant, were all at least .4 or higher for the detail pages.

Table 5: Statistically significant correlations of interest indicators with explicit user interest assessment. All values except mean correlation (values between -1 and 1) are in absolute numbers (out of 22 mobile users), measured for the news overview page and detail page. Correlations not statistically significant for overview and detail pages are not included (if significant only for overview or detail page, the values for the respective other are replaced by "-").

Indicator	Ø Correlation		# Significant		Corr. < .2		Corr. < .4		Corr. < .6		Corr. < .8		Corr. >= .8	
	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail	Overview	Detail
Visibility Count	.71	-	5	-	0	-	0	-	2	-	1	-	2	-
Visibility Seconds	.55	-	2	-	0	-	0	-	1	-	1	-	0	-
Contact in Fragment	.84	.73	4	5	0	0	0	0	0	2	2	1	2	2
Contact on Same Y Count	.65	-	2	-	0	-	0	-	1	-	1	-	0	-
Visible Before Swipe	.76	.64	3	6	0	0	0	0	0	1	2	2	1	3
Visible After Swipe	.53	.45	1	8	0	0	0	0	1	0	0	6	0	2
Skipped While Swipe	39	.64	1	6	1	0	0	0	0	1	0	2	0	3
Orientation Change Landscape	-	.45	-	8	-	0	-	0	-	1	-	5	-	2

6 DERIVED USER MODELS

Based on our first insights related to implicit interest indicators and their relevance for individual users and groups of users, we suggest a generalizable formula as base user model, considering all indicators for which a significant correlation between implicit and explicit interest indicators and statements was found. Second, we show an exemplary application of this idea by reporting the computed results for individual instances of the formula for certain users (we demonstrate this step for a small sample of representative desktop and mobile users). The formula per user considers only those indicators where significant positive correlations have been found for this particular user. It can be generally described as a weighted average as it is has been traditionally used for computations of rating predictions in neighborhood-based recommender systems (see e.g., [18]). It is explained in further detail as follows. Equation 1 shows the computation of predicted interest for a specific user in a certain article where n is the number of significant correlations between implicit indicators and explicit interest statement. Both detail and overview pages are considered for the computation. v_i is the user's normalized value for the implicit indicator. The values are normalized to a value between 0 and 1, based on the user's concrete values for this indicator for all detail or overview pages, see Equation 2. $corr_i$ is the user's correlation (in our example Pearson's r) for a specific significant indicator. We consider this formula a general suggestion that does not necessarily need to be directly related to the indicators used in our study or Pearson's r for correlation. It could easily be adapted to other scenarios.

$$Pred_{interest} = \frac{\sum_{i=1}^{n} v_i * corr_i}{\sum_{i=1}^{n} corr_i}$$
(1)

$$v_i = \frac{v_{orig} - v_{min}}{v_{max} - v_{min}} \tag{2}$$

To get a feeling for the applicability of this idea, we computed predicted interest values for the articles for the participants of our study. For these samples, we found a relatively close match between predicted and explicit values in most cases. This indicates that our approach bears potential to be able to actually predict interest. However, further robustness tests need to be conducted to verify the correlations. Table 6 shows example results for the predicted interest based on the implicit interest indicators and the related explicitly provided user interest for a small sample of selected users and articles. Thus, the table allows for a comparison between predicted interest based on implicit interest indicators and explicit statements. For reasons of better comparability, we translated the users' statements (provided using a seven-point Likert scale) to a value range of 0 to 1. The value range does not consider a user's individual rating behavior (thus, the range is equal for all users). Table 6 includes an example where this might be misleading at first glance because this user's personal minimum was 3 (instead of 1 as for most of the other users). The examples displayed in Table 6 were selected as follows: for both environments, desktop and mobile, we selected representative users with either a lot of indicators where we could find significant correlations or only very few significant correlations. From the predicted interest in certain articles, we later want to be able to derive more common interest in certain topics that are associated with the articles. Further, we envision using the predicted interest in certain articles from reading behavior to derive interest in articles that can be considered similar (either based on

Table 6: Examples for predicted interest values in comparison with users' explicit statements. We show exemplary predictions for two desktop and two mobile users (one with many, one with only few significant correlations) and two exemplary articles.

User	Artic	ele A	Article B			
	Predicted Explicit		Predicted	Explicit		
Desktop						
U1 - Many sig. correlations	0.3	0.33	0.61	0.67		
U2 - Few sig. correlations	0.02	0.33 ¹	1.00	0.83		
Mobile						
U3 - Many sig. correlations	0.01	0.17	1.00	1.00		
U4 - Few sig. correlations	0.10	0.17	0.59	0.83		

¹ The value of 0.33 corresponds to the value 3 provided by the user which was this user's personal minimum.

meta data or content). For more considerations on future work, consider Sections 7 and 8.

7 DISCUSSION

Our analysis (and prototype) contributes to the existing body of knowledge on implicit interest indicators as basis for web content recommendation. It constitutes an update to existing findings of earlier, similar studies for two reasons. First, it revisits known concepts using up-to-date web technology (including state of the art frameworks) for the analysis of client-side interactions which also led to a higher number of indicators. Second, it introduces mobile interactions which have not been considered yet in any of the earlier studies discussed in Section 2. Comparing the mobile setting to the desktop setting, it has to be noted that the mobile setting poses certain challenges. On the one hand it is challenging to precisely and reliable cover the indicators on the huge amount of different mobile devices. On the other hand, fewer indicators can be gained in the mobile setting since no movement-based indicators may be obtained, aggravating a trustworthy derivation of user interests. However, the obtained indicators generally showed a higher correlation and significance in our study setting than the ones on the desktop.

While we acknowledge that the reliability of the results of our study might be limited due to the moderate number of participants in the two groups, we consider them important first insights that point to interesting directions and seem to indicate that our approach has potential to be able to predict user interest. For instance, our first results suggest that the *predicted user interest* based on implicit indicators is relatively *close to the users' explicit interest statements*. Thus, the derived user models seem appropriate for further consideration in web content recommender systems. Further potential limitations are discussed as follows.

One issue related to the design of our news page is a potential *bias* based on the *position* of the respective fragment. This bias is reported by several studies (see e.g., [3, 14]) and implies that users are more likely to read text that is positioned at top of a page. A potential solution would have been to randomize the order of the fragments on the overview page which would however have lead to implementation-related difficulties (e.g., for the identification of items skipped while swiping). Further, we (intentionally) *reduced* the content of our news page to *plain text* in order to avoid side effects related to design, position or type of multimedia elements. It is conceivable that for other types of content the significance of individual interest indicators differs from what we report for text content.

On the news detail pages, our study considered the full text as one page fragment. To allow for a more fine-grained analysis, the page could be further split up into a higher number of fragments (this is generally already possible with our prototype and considered for future work). Further, our study investigated a *rather static* page. Contemporary websites are often more dynamic (e.g., single page applications with heavy use of asynchronous data loads). Full support for such websites would require changes in the implementation which might affect the functionality of certain indicators. Additionally, currently we focused on the individual analysis of certain indicators only, but did not consider certain sequences or combinations of indicators that might exhibit specific semantics. For example, on mobile phones it is often hard to reliably distinguish between clicking and swiping resulting in unintentional clicks that are immediately followed by a click on the back button. Detecting such sequences might help to avoid counting false positives.

Finally, a more general limitation is related to the well-known cold start problem (see e.g., [13]). Our suggested procedure for the prediction of user interest (see Section 6) relies on users' explicit feedback to identify their individual implicit indicators on at least one occasion during system use. This is not generally uncommon to tackle the cold start problem. For instance, popular recommendation services such as Netflix⁹ rely on explicit feedback which is usually collected upon registration at the system to provide high-quality recommendations before enough implicit information is available. Nevertheless, we believe that future work should also investigate alternatives. For instance, it might be possible to create a "default user model" or "group model" comprising only the indicators which have been proven to be relevant for the majority of all users so far. This default model could then be stepwise refined for individual users as more information is revealed to the system during longerterm use. Such a default model would however have to be validated by a study with a high number of users first, in order to make sure the findings can be considered reliable.

8 CONCLUSIONS

In this paper, we discussed the analysis of implicit indicators for user interest on a web site based on client-side analysis of reading behavior. We presented a prototypical technical infrastructure and concrete application as well as the design and results of an online study with desktop and mobile users. Although client-side analysis of reading behavior and derivation of implicit interest indicators have been researched before, our work exceeds the state of the art in several ways (see Section 1). Our work can be seen as a first step in the development of web content recommender systems based on such indicators. Future work should include a subsequent analysis with a higher number of samples in order to gain statistically more reliable results. Additionally, we plan using the approach, indicators and general model structure presented in this paper to further analyze the data with different correlation measures (e.g., Spearman's rank correlation). In the future it is also envisioned to utilize the user models we suggested in combination with extraction of information from the content itself. Our approach potentially enables a system to determine which content is of interest for a user. Through further information extraction, a system could derive relevant meta-data (e.g., length or source of a text or what genre it belongs to) and then recommend similar content. We believe that implicit, unobtrusive client-side interest analysis has high potential to provide high-quality recommendations on intelligent web sites while not requiring too much activity and attention from the user.

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⁹https://www.netflix.com

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