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IMPACT OF COVID-19 PANDEMIC ON USER SEARCH BEHAVIOR: A CASE STUDY OF POSTGRADUATE STUDENTS

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Abstract: Relevance Feedback (RF) is crucial for building a user profile which is a fundamental element of different intelligent systems such as information retrieval, information filtering, and personalization. RF is affected by a number of contextual factors such as mood, stress level, and sentimental state of the user. Covid-19 pandemic imposed dramatic changes to the user environment as well as the search context. This paper investigates user's search behaviour to identify the differences in the behavior between the contexts before and during the Covid-19 pandemic. This can be practically translated into identifying the differences in the relationship between the implicit feedback and the explicit relevance level between the two contexts. For this purpose, we conducted three user studies (i) Pre-COVID-19, (ii) Mid COVID-19 and (iii) after Covid-19. A user study was conducted on the same group of users on the three user studies. The Pre-COVID-19 user study took place before the pandemic started and the Mid-COVID-19 user study took place three months after the beginning of the pandemic. After Covid-19 stage took place after 18 months of the pandemic. A linear regression model was developed for each user study using IBM-SPSS. The analysis showed a significant variation in the user behavior between the two studies due to the COVID-19 context and its impact on user search behaviour. Also, two new RF parameters in Mid-COVID-19 were shown to have a significant relationship with the explicit user interest which were Mouse Clicks and Page/Down strikes. Furthermore, the comparison between the two models showed that the second regression model achieved a higher accuracy level that is attributed to the common behavioral change imposed by the pandemic.

INTRODUCTION

The widespread of recommender systems (RSs) and their applications in different areas such as search engines, online shopping, social networks, and others, brings the concept of Relevance Feedback (RF) to the attention as it is the raw material for building a user profile, which is the cornerstone of recommender systems. RSs are also linked to the concept of personalization that is concerned with customizing the results of a system to individual users' preferences and profiles. The personalization process can only be done through RF collection and utilization. Also, RF is paramount for the performance enhancement of intelligent systems as these systems can learn from their user's feedback and adapt to provide better performance. Search engines are one of the main application areas where RF can be utilized to enhance both the accuracy of the search performance and the user experience.

In general, RF can be defined as the collection of information from users on how relevant a

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specific item is to their interest [1], [2]. RF is collected from users to identify their behavior and opinions regarding a specific item or service, which makes it sensitive to the search context in which it was collected including the domain, application type, and psychosocial and emotional factors.

Covid-19 pandemic imposed dramatic changes to the user environment as well as the search context which includes -but is not limited to- lockdowns, social distancing, serious health issues, and the resulting unpreventable adverse economic and financial concerns. Taking into consideration the importance of RF, the fact that it is contextual-sensitive, and the major changes the pandemic has brought to the user environment, it becomes imperative to investigate the potential consequent changes in the relationship between RF and user interest.

This paper is an attempt to identify the differences in the users' behavior concerning their interest level between the contexts before and during the Covid-19 pandemic. This can be practically translated into identifying the differences in the relationship between the implicit feedback and the explicit relevance level between the two contexts. To achieve the purpose of this paper, a user study was conducted on a group of postgraduate students. The study was carried out in three separate stages; the first stage was conducted before the pandemic started and the lockdown took place, the second stage was undertaken after three months from the beginning of the pandemic, and the final stage (i.e. Post covid-19) occurred after 18 months of the beginning of the pandemic.

The main contribution of this paper is enriching the body of knowledge by providing two regression models for predicting the user interest level from the implicit feedback parameters. The first regression model represents user behavior in the normal situation where the students search for the information from the university, while the second regression model represents user behavior in the exceptional and unordinary situation associated with the pandemic. Furthermore, the paper identified the differences in user behavior based on the contextual changes as it compared user behavior before and during the pandemic.

Related Work

RF is classified into explicit and implicit [3] [4] [5]. However, these two categories are different as explicit feedback is limited while implicit feedback is rich and diverse. Explicit feedback is considered more accurate when compared to implicit feedback in reflecting the relevancy of the retrieved document or object to the user's interest. Additionally, explicit feedback represents positive and negative user judgment on the retrieved information (e.g. like/dislike, useful/not useful), whilst implicit feedback only symbolizes positive judgment [6].

Explicit feedback parameters were usually captured by asking the user explicitly to provide feedback to denote the relevance of the document according to their information needs. Additionally, explicit feedback could be provided in the form of a scaled number (e.g., positive/inverse", "relevant/non-relevant", or like/dislike). Annotation and/or some forms of tagging could also be used to provide more information about the viewed document [3].

On the other hand, implicit feedback inconspicuously obtains the required information about users' behaviour by recording their interactions with the system. Some commonly used techniques to gather implicit feedback are dwell time, saving, scrolling, bookmarking, printing and click-through. Despite the useful and large amount of implicit information that can be gathered without even asking users for any additional activities, inferences drawn from implicit feedback are seen

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as less reliable when compared to explicitly gathered data [7].

The connection between a user's interest and relevance feedback as well as the relationship between implicit and explicit feedback was thoroughly studied by many researchers to identify which implicit feedback parameters best reflected the user interest and could be beneficial to construct a user profile. For instance, to know how implicit relevance feedback is utilized to build a user profile, [8] investigated user behaviour when reading news articles. Their study was conducted on eight users who were asked to read news articles, which were available on Internet discussion groups (e.g., USENET news), and then to give a rating depending on their level of interest in the articles they read. The main findings of the study were that reading time was strongly correlated with the user interest while saving, following up, and copying was found not strongly associated with the user interest.

In their research, [9] aimed at identifying the implicit feedback parameters that could be considered as major indicators of user interest and be linked with explicit relevance feedback. Their study was conducted on 75 students who were asked to use a customized web browser for unstructured browsing. The browser was meant to capture implicit parameters of relevance such as mouse clicks, combined scrolling, and time-on-page as well as to capture the explicit relevance rate for each visited page. It was found that time spent on a page along with the amount of scrolling were strong indicators of interest. Conversely, mouse clicks and individual scoring indicators were found to be ineffective predictors of the explicit relevance rating.

By carrying out a study on academic and professional journal articles and abstracts, [10] further categorized implicit relevance feedback parameters into four main groups namely examine, retain, reference, and annotate. These four categories could then be sub-classified based on the scope of the visited information (i.e., segment, object, or class). It was concluded that printing and reading time were strong implicit predictors of the relevance level of the article and that the user spent a longer time reading academic articles than news stories.

Reading time as an implicit relevance parameter was further examined and adopted as a document re-ranking technique [11]. Their technique used the reading time captured from the user's interaction along with the search results to automatically re-rank the retrieved documents, which were later presented to the users as summaries. The display was further updated based on the captured reading time.

In [10], categorization of the implicit relevance feedback parameters was extended to include a new behaviour category called "Create" in a study performed [10]. The new behaviour category accompanied the implicit parameters pertaining to the user behaviour when creating or updating information. Some additional parameters were added to the existing categories that were originally proposed by [10].

It has been argued that click-through data could contain useful information regarding the relevance of the visited pages as users normally do not click on links randomly. [13] measured user activity and collected explicit relevance judgments based on Web search. They found that the best retrieval model was the combination of click-through, dwell time, and the way a user ended a search session. In a study conducted by [14] on click-through data in web search, it was found that click-through data was an expressive and reliable, but biased source of implicit feedback. However, the relative user preferences, which were derived from the clicks, were found to be relatively accurate. This notion is supported by other studies that demonstrated the positive

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effects of click-through data in estimating the users' interests [15] [7] [16].

In page visit literature review, "re-finding" is a term used to denote the Post-Click Behaviour (PCB) in which users return to the same web pages that they have already visited. [17] studied the post-click behaviour to predict the user interest and they found that approximately 38% of all user queries were used to re-find a previously visited page. In addition, the results showed that queries that were used to re-find a page were better than those that were previously created to find the page. In the same context, [17] found in their experiments that the retrieval performance could be enhanced using re-finding based predictions for the relevant page/s in the personalized search.

The PCB term was also introduced by [18] to indicate the behaviour of users during the dwell time (time spent reading the information retrieved). The experiments showed that post-click parameters, such as mouse movement on the page and combined scrolling, together with the dwell time were useful for enhancing document relevance prediction. The proposed method was shown to be more effective in estimating the document relevancy than using dwell time solely.

[19] postulated that text selection actions on the visited page could represent the user's interest level in the visited page and thus enhance the retrieval performance. The proposed approach is based on the fact the text selection activities performed by the user can be used as an indication of their level of interest. This approach was proved to be effective in significantly enhancing the retrieval performance.

[20] analyzed users' behaviours such as clicks, hovers, text selection, and cursor trails on the Search Engine Result Pages (SERPs), and used this information to cluster the users based on the similarity of their behaviour.[21] proposed an integrated implicit feedback model to improve the post-retrieval document relevancy. They combined dwell time, click-through, page review, and text selection. Their study found that using all these parameters in a single model provides advantages over just using dwell time, click-through, page review, and text selection alone. Furthermore, it was also found that text selection had the highest accuracy compared to other commonly used and extensively researched techniques including dwell time and click-through. This indicates that user' post-click behaviours can be efficiently used to improve document relevance prediction.

[22] studied the relationship between different implicit feedback parameters and the interest level of the user in a specific document. The study concluded that dwell time, mouse clicks, and mouse movement can significantly indicate the user interest level. However, Dwell time was the most important parameter among them. Additionally, [8] found out that there is a correlation between the time spent on a page and the user explicit rating for that page. [23] postulated that although mouse movements and scrolling, selecting, highlighting besides key presses can be tracked and collected, only Dwell time seems to significantly indicate the user's rating for a specific document. Furthermore, when investigating the relationship between relevance feedback and user satisfaction concerning the visited document during a web-based question answering task, dwell time was considered as the most important implicit feedback parameter indicating the user's interest in the visited document [24]

In sum, relevance feedback literature shows that a wide array of implicit relevance parameters can be used as indicators of the user's interest level in assessing the document relevance in relation to their information needs. Nevertheless, there is a lack of consensus on a specific

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combination of parameters to be used to estimate the user interest level for a document or an item. Additionally, user behaviour could shift responding to changes that occur in the search environment or to the nature of the required information. Differences in the interest levels of users could also be contributed to behavioural disparities.

USER STUDY

As discussed in the introduction section, this paper aims to identify those post-visit relevance feedback parameters which correlate most with the user interest in a document with a specific population of postgraduate students. In addition, it aims to investigate the probable change of the correlation between the post-visit relevance feedback parameters and the user interest in the context of the Covid-19 pandemic and the consequent shift to the distance learning style.

To achieve the aim of this study, three user studies were designed and conducted to capture the user's feedback before, during and after the Covid-19 (18 months from the beginning of the pandemic) crisis for comparison purposes. The two studies were conducted on the same students and the same classes. An adjusted structured observation technique was applied similarly to [25] [26] in which 200 postgraduate students were invited to perform predefined information-seeking tasks related to their courses. In each course the students were asked, by their lecturers, to answer a 5-question quiz during the lecture, and they were allowed only to use the provided search engine which is designed to capture the user search behaviour. The search facility allowed the user to select the question number, view the question text, and perform the search process to find the right answer from the students' point of view. During the search process, the system captured the students' search behaviour including the implicit and explicit relevance feedback that was stored in a database. The study was conducted at different stages, firstly the study took place at the beginning of the second semester of the academic year 2019-2020, which was ultimately the beginning of the widespread of Covid-19 pandemic in Jordan and then reconducted at the end of the same semester while students were studying from home due to the Covid-19 resulting restrictions. The third phase took place in the beginning of the first semester of the academic year 2021/2022, after almost 18 months of Covid-19 pandemic.

Participants

A group of 200 postgraduate students (113 females and 87 males) in 8 classes were invited to participate in the user study as shown in Table 1. The students were given an induction on the quiz they are required to answer and how to use the dedicated search engine to answer the question and to find the relevant information.

Table 1: Participants' Characteristics

Characteristic		#Of Participants
Gender	Female	113
	Male	87
Class	Research Methods	30
	Information & Business Strategy	25
	Advanced Database Systems	24
	Advanced Computer Networks	20
	Advanced MIS	21

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Advanced Software Engineering	28
Knowledge Management (KM)	24
Diversity Management	28

Document Collection (Corpus).

The document collection used for the user study consisted of 10,000 documents. It was designed and created to suit the purpose of the study as it included the questions (search tasks), their predefined relevant documents, and non-relevant documents as well. The document collection was developed in collaboration with the course lecturers who were responsible for creating the questions and preparing the relevant documents, in addition, to provide the non-relevant documents as well. The resulted corpus contained different document types such as Microsoft Word, PowerPoint presentations, PDF, and Microsoft Excel.

Search Tasks (Questions)

Each lecturer of the participated classes was asked to write a quiz of five questions and provide a few relevant documents, which contain part of the answer. The questions and their relevant documents were uploaded to the system to make it ready for the participants to use. Table 2 shows an example of the questions and their relevant documents.

Table 2: Example of The Questions and Their Relevant Documents

Class		Q_Text	Relevant Docs
KM	1	Explain the Main KM Processes	1. Introduction_to_KM. pptx 2. Ch4 KM Process.pptx 3. Knowledge management and organization. Pdf
	2	Compare between explicit and tacit knowledge.	1. Introduction_to_KM. pptx 2. Knowledge Types .pptx 3. Knowledge representation. Pdf

USER STUDY EXPERIMENTAL SETUP

The search user behaviour capturing and monitoring tool Azra, has been used as a platform for conducting the used study. Azra has been developed at Mutah University for academic research purposes to facilitate capturing user implicit and explicit relevance feedback during the information-seeking process. It is designed to capture different relevance feedback parameters such as user query, dwell time, mouse clicks, mouse movements, key up, key down, print, explicit relevance rating. In addition, it enables the uploading, indexing, and searching for any document collection and supports most of the known document's extensions. The tool is based on the well-known Lucene [27] [28] search library which is widely used in the search technology. As Azra is developed for academic research purposes, as shown in Figure 1, it supports the task-based search process as it allows the user to select a specific task to complete and link the collected data to the task and the user.

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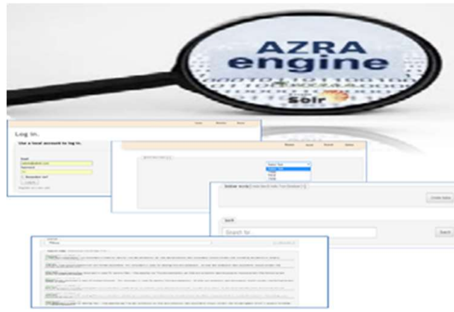

Figure 1:Azra Search Engine

Experimental procedure

The lecturers have been trained on the experimental procedures including how to use the search system to answer the quizzes. The lecturers in turn explained to their students what is requested from them and demonstrated how to use the search system. Afterward, the students of each class were provided with the quiz questions and asked to solve them using the provided search system. During the search process, the feedback capturing component of the system was actively collecting the relevance feedback from the students and saving them in the database.

Collected Data

As discussed in the related work section, there is a wide array of relevance feedback parameters that may indicate the user interest. However, the current paper focuses more on the post-visit parameters as they are more suitable for the domain, scope, and limitation of the study. Furthermore, this paper comes in series of other related research in the field of enterprise search and user relevance feedback, which used the same relevance feedback capturing tool focusing on the post-visit parameters. The collected relevance feedback parameters are described in Figure 2.

Document	
Dwell Time (Time on Page)	The actual time that the user spent on the page. This means the time is only counted when the window is On and Focused.
Copy Count	The number of the copy instances (if the user copied part of the text of the document).
Mouse Click Count	The number of mouse clicks on the page whether they were on internal links or the other areas of the page
Mouse Movement Count	The number of movements of the mouse on the page
Page Up /Down Press Count	The number of times that these keys were pressed
Up/ Down Arrow Press Count	The number of times that these keys were pressed
Up/ Down Arrow Press Holding Time	The time spent holding these keys
Mouse Scrolling Count	The number of mouse scrolls on page
Scroll Bar Click Count	Number of the number of the clicks on the scroll bar
Scroll Bar Holding Time	The time spent clicking scroll bar
Bookmark	If the page was bookmarked
Save	If the page was saved
Print	If the page was printed
Explicit Relevance Level	The user judgment on how relevant this page was their query. An integer number between 1 and 10

Figure 2 Relevance Feedback Parameters

The collected dataset of the first part of the study, which took place before Covid-19 pandemic consisted of 1589 data instances each of which represents the relevance feedback captured for a documented visit. The dataset for the second part consisted of 1816 data instances. Table 3 shows a sample of the collected data. The third part of the study consisted of dataset, which included

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(2047) instances after the Covid-19 pandemic

Table 3: Sample of the collected data

UserName	IndexFile	FileName	TaskI	TaskName	QueryText	QueryTime	MouseClickCount	MouseMover	MouseScr	Explicit	DwellTime
120150304070@mutah.	17209	notation more f	6	what is the Asymptotic ana	Asymptotic	46:55.4	0	213	0	5	00:04.9
120140314051@mutah.	15970	Asymptotic Algc	6	what is the Asymptotic ana	Asymptotic	43:06.9	0	80	0	1	00:03.4
120150304067@mutah.	16747	How does asym	6	what is the Asymptotic ana	what is the As	45:47.9	0	173	23	4	01:49.0
120140304003@mutah.	15826	A Brief History c	7	hat is the complixty time fc	sort	46:14.6	0	105	162	5	00:26.3
120150304070@mutah.	15972	Asymptotic perf	6	what is the Asymptotic ana	Asymptotic	46:55.4	1	1993	25	5	01:50.6
120150304034@mutah.	16747	How does asym	6	what is the Asymptotic ana	asymptotic an	44:16.8	0	37	0	5	00:02.8
120140314051@mutah.	15973	asymptotic runr	6	what is the Asymptotic ana	Asymptotic	43:06.9	0	55	0	1	00:02.9
120140304020@mutah.	17008	London Ambula	7	hat is the complixty time fc	merge	46:50.6	0	708	167	3	00:24.6
120140314033@mutah.	16843	Introduction to	6	what is the Asymptotic ana	Asymptotic an	45:16.9	0	53	0	5	00:02.3
120140314051@mutah.	15974	Asymptotic.ppt	6	what is the Asymptotic ana	Asymptotic	43:06.9	0	33	0	1	00:02.0
120140304041@mutah.	16887	khaled essy.doc	7	hat is the complixty time fc	time	47:07.6	0	87	80	5	00:09.4
120150304018@mutah.	16451	Dynamic Memo	8	what is the C++ key word tc	array	45:07.7	0	287	0	5	02:41.3
120140314051@mutah.	16646	first task .pptx	6	what is the Asymptotic ana	Asymptotic	43:06.9	0	84	24	5	02:09.6
120150304034@mutah.	15972	Asymptotic perf	6	what is the Asymptotic ana	asymptotic an	44:16.8	0	473	0	5	01:45.7
120140304040@mutah.	17392	running time m	6	what is the Asymptotic ana	asympototic a	40:50.0	0	47	0	5	00:59.3
120140314033@mutah.	15970	Asymptotic Algc	6	what is the Asymptotic ana	Asymptotic an	45:16.9	0	141	0	5	00:36.6
120140314024@mutah.	16887	khaled essy.doc	7	hat is the complixty time fc	time merge	47:26.5	0	14	0	2	00:01.9
120140304041@mutah.	15974	Asymptotic.ppt	7	hat is the complixty time fc	time	47:07.6	0	64	0	5	00:02.8
120140314047@mutah.	15970	Asymptotic Algc	6	what is the Asymptotic ana	Asymptotic	47:23.7	0	244	24	3	00:29.7
120150304050@mutah.	17392	running time m	7	hat is the complixty time fc	merge	46:39.9	0	162	24	4	00:13.1
120150304030@mutah.	15990	base case.docx	5	what is the induction?	Algorithem inc	33:43.2	0	21	0	5	00:02.4
120140304041@mutah.	16646	first task .pptx	7	hat is the complixty time fc	time	47:07.6	0	93	0	5	00:22.7
120140304015@mutah.	15973	asymptotic runr	6	what is the Asymptotic ana	Asymptotic	46:44.7	0	22	0	3	00:02.2

Figure 3User Study Experimental Set-Up

Data Analysis and Results

As discussed in the user study section, the data collection was conducted on three user studies from the same students group. The pre-COVID-19 was conducted before Covid-19 and took place in the university using the university computer labs. Mid COVID-19 was conducted three months from the beginning of the pandemic in which students were asked to perform search tasks from home due to the lockdown enforced by the public authorities. The third user study was conducted after the pandemic (post stage) of almost a year In this section, we discuss the analysis and results of Pre COVID-19 , Mid COVID-19 and Post Covid19. Finally the results of the three user studies were compared to find out if there are any differences in the user search behaviour before, during and after the pandemic and its consequent contextual changes.

For each study, as shown in Figure 2, the data collection platform Azra collected 13 post-visit implicit feedback parameters in addition to the explicit relevance level. The unused parameters, which are parameters with null or zero values for all instances have been excluded from the analysis. The remaining parameters were analyzed using the IBM SPSS statistical analysis package to create a linear regression model.

The Linear regression models usually include three categories of parameters; Coefficients (β) which are the constants, Predictors (X), and the Target (Y) as shown in Equation (1) [29].

$$Y \approx f(X, \beta) \qquad (1)$$

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For the Linear regression with multiple predictors (N), the model can be formalized as shown in Equation (2) [29].

$$\hat{Y} = \beta_\circ + \sum_{i=1}^{N} \beta_i X_i \qquad (2)$$

Where Y ̂ is the fitted predicted value of the dependent variable, β_°is the intercept, β_i is the variable coefficient, X_i is the value of an independent variable, N is the number of the independent variables.

Pre COVID-19 (before Covid-19)

Linear Regression Analysis

Table 4 reveals that there is a significant effect of the mouse movement count, mouse scrolling count, and dwell time on the explicit relevance level. The analysis also showed that dwell Time is the most important implicit feedback predictor of the explicit feedback followed by the Mouse Scrolling Count, while the Mouse Movement Count was the least important implicit predictor. Table 4 shows the Linear regression model components

Table 4: Linear Regression Model Pre COVID-19

Parameter		Coefficient		Sig.	Importance
Intercept	-	.208	($\beta_\circ$)	0.00	-
Dwell Time	(X_1)	.554	(β_1)	0.00	0.645
Mouse Scrolling Count	(X_2)	.408	(β_2)	0.00	0.352
Mouse Movement Count	(X_3)	.028	(β_3)	0.001	0.003

Linear regression is mathematically expressed as shown in Equation (1) and in order to calculate the predicted value of the explicit feedback based on the values of the implicit feedback parameters we substitute the value in Table 4 into Equation (2) to have Equation (3).

$$\hat{Y}=0.208+(0.554\times X1) + (0.408\times X2) + (0.028\times X3) \qquad (3)$$

IBM SPSS-Statistics generates an automated importance value for each predictor in the model which is used to normalize the equation. The product of using this value in Equation (2) is Equation (3) Then the importance of each predictor is used to normalize the value:

$$\hat{Y}=0.208+(0.554\times 0.645 \times X1) + (0.408\times 0.352 \times X2) +(0.028 \times 0.003\times X3) \qquad (4)$$

Linear Predictive Model Validation

As shown in Table 5, linear regression model accuracy in predicting the explicit feedback from the implicit parameters was 84.5%. the accuracy is calculated automatically by the statistical analysis package and based on R-Squared (R2) method which is commonly used for linear regression validation.

Table 5:Sum Squares For The Linear Model Pre COVID-19

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Source	Sum of R-Squares	df.	Mean Square	F	Sig
Corrected Model	**3,160.468**	**3**	**2,896.019**	**9,052.348**	**0.00**
Residuals	**576.942**	**1,586**	**0.364**		
Corrected total	**3,737.409**	**1,589**			
Accuracy	**84.5%**				

Mid COVID-19 (Three Months After the Beginning of the Pandemic)

Linear Regression Analysis

The same procedure of Pre COVID-19 was applied for the analysis of Mid COVID-19 data. As shown in Table 6, there were two new parameters that significantly affected the explicit relevance level: Page Up /Down and Mouse Click Count. However, the correlation coefficient value between Page Up /Down and the explicit relevance level is negative which reflects an inverse relationship.

Table 6: Linear Regression Model Mid COVID-19

Parameter		Coefficient		Sig.	Importance
Intercept	-	0.763	$(\beta_\circ)$	.000	-
DT-Scaled	(X_1)	0.427	(β_1)	.000	0.423
Mouse Click Count	(X_2)	0.366	(β_2)	.000	0.315
PageUp /Down Press Count	(X_3)	-0.189	(β_3)	.000	0.164
Mouse Scrolling Count	(X_4)	0.126	(β_4)	.000	0.067
Mouse Movement Count	(X_5)	0.068	(β_5)	.000	0.030

Substituting the values in Table 6 , Equation (5) results:

$$\hat{Y}=0.763+(0.427\times 0.423\times X1) + (0.366\times 0.315\times X2) - (0.189\times 0.164\times X3) + (0.126\times 0.067 \times X4) + (0.068\times 0.030 \times X5) \quad (5)$$

Linear Predictive Model Validation

As shown in Table 7, linear regression model accuracy predicting the explicit feedback from the implicit parameters was 94.4%.

Table 7: Sum Squares for The Linear Model Mid COVID-19

Source	Sum of R-Squares	df.	Mean Square	F	Sig
Corrected Model	**3,296.468**	**5**	**659.239**	**6,147.585**	**0.000**
Residuals	**576.942**	**1,811**	**0.107**		
Corrected total	**3,490.400**	**1,816**			
Accuracy	**94.5%**				

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Linear Regression Analysis

The same procedure of Pre COVID-19 and Mid-COVID-19 were applied for the analysis of After COVID-19 data. As shown in Table 8, there was one new parameter that significantly affected the explicit relevance level: Copy with 8% of importance. As noted from Table 8 the correlation coefficient value between Page Up /Down and the explicit relevance level is still negative, which indicated an inverse relationship.

Table 8: Linear Regression Model After COVID-19

Parameter		Coefficient		Sig.	Importance
Intercept	-	.233	$(\beta_\circ)$	0.000	-
Dwell Time	(X_1)	.256	(β_1)	0.000	0.6430
Mouse Scrolling Count	(X_2)	.130	(β_2)	0.000	0.1674
Mouse Movement Count	(X_3)	.440	(β_3)	0.000	0.0036
Mouse-Click-Count	(X_4)	.142	(β_4)	0.000	0.1035
Page-Up-Down	(X_5)	-.192	(β_5)	0.000	0.0015
Copy	(X_6)	.233	(β_6)	0.000	0.0810

Linear regression is mathematically expressed as shown in Equation (1) and in order to calculate the predicted value of the explicit feedback based on the values of the implicit feedback parameters we substituted the value in Table 8 into Equation (2) to have Equation (6).

$$\hat{Y}==0.233+(0.256\times X1) + (0.130\times X2) + (0.440\times X3)+(0.142\times X4)-(0.192\times X5)+(0.233\times X6) \quad (6)$$

the importance of each predictor is used to normalize the value by substituting the values in Table 8, Equation (7) results:

$$\hat{Y}=0.233+(.256\times 0.643\times X1) + (0.130\times 0.167\times X2) + (0.440\times 0.004\times X3) + (0.142\times 0.104\times X4) - (0.192\times 0.002\times X5)+(0.233\times 0.081X6) \quad (7)$$

Linear Predictive Model Validation

As shown in Table 9, linear regression model accuracy predicting the explicit feedback from the implicit parameters was 98.4%.

Table 9: Sum Squares for The Linear Model After COVID-19

Source	Sum of R-Squares	df.	Mean Square	F	Sig
Corrected Model	**3,296.468**	**5**	**659.239**	**6,147.585**	**0.000**
Residuals	**576.942**	**1,811**	**0.107**		
Corrected total	**3,490.400**	**1,816**			
Accuracy	**98.4%**				

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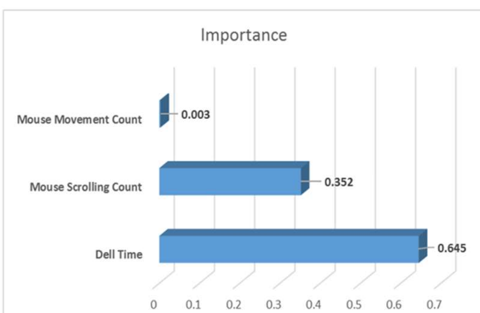
Comparison

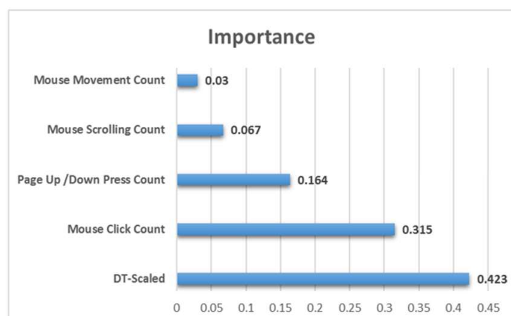
This section provides a comparison between the results of the data analysis of the situation before Covid-19 (A), three months after the beginning of it (B), and 18 months after the beginning of the pandemic (C). The diagram below includes two models of the most significant implicit feedback parameters that reflect the explicate relevance level associated with their importance.

Figure 4 shows that in situation A, the significant implicit parameters that demonstrated a significant effect on explicit feedback were only the Dwell Time, Mouse Scrolling Count, and Mouse Movement Count. However, in situation B, in addition to the former three implicit parameters, there were two additional implicit parameters that revealed a significant effect on the explicit feedback, which were Page Up /Down and Mouse Click Count. Additionally, in situation C, an additional implicit parameter (Copy) demonstrated a significant impact on the explicit relevance feedback. Taking into consideration that the data were collected from the same group of users, the inclusion of other new parameters indicates a significant change in the student's behaviour while conducting information-seeking tasks. This change in students' search behaviour could be attributed to the improved level of students' experience and insights in searching the required information from the datasets after approximately a year and half of a new form of electronically driven teaching and learning process that necessitated better information search and reporting skills.

A: Before Covid-19



B: Three Months during Covid-19



C: 18 months after Covid-19 pandemic

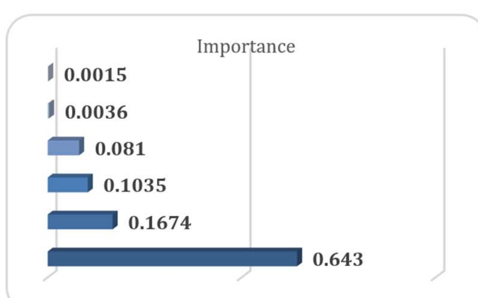


Figure 4 Comparison of Implicit Parameters Importance

Although the explanation of this change might need a further investigation, it could still be

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explained in the context of Covid-19 pandemic and its associated changes in the user environment such as the high stress and psychological anxiety on people resulting from the pandemic and its consequent unusual actions. [30] Investigated the user behavior under pressure and found out that there is a significant relationship between the stress level and the mouse click count. In the same context, [31] also indicated that there is a relationship between the stress level and the Keyboard and Mouse strikes.

For example, the Mouse Click Count, which has a significant effect on the explicit feedback, could be linked to stress. Students do more mouse clicks as they are getting more interested in the document under the effect of the stress level inherited from the pandemic environment. Page Up /Down, which has an inverse relationship with the explicit feedback, could be also explained in the context of the pandemic as the stress level might make the student to be less patient in finding the right information and consequently to find the relevant document faster especially if they encounter seeking in those documents that appear to be irrelevant to their searches.

Figure 5: Accuracy Comparison

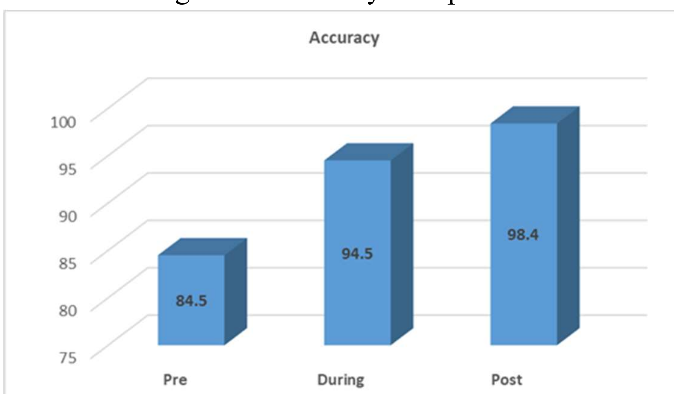

Figure 5 Accuracy Comparison

The importance of the implicit feedback parameters also changed between situations A and B. for instance, the importance of the dwell time decreased from 0.546 to 0.423. Furthermore, the importance of the mouse scrolling count decreased from 0.352 to 0.067 affected by the entrance of the mouse click count with relatively high importance of 0.315.

The results in Figure 5 shows that the accuracy of the linear regression model increased from 84.55 in situation A to 94.4% in B and this logically can be justified by the common user behaviour imposed by the changes the pandemic brought about to the user environment including stress, more freedom in the search process as the user carried out the search tasks from home and also the search skills they obtained during the three months period of time studying from home and relying on internet based search and study. This trend is also intensified after the pandemic of almost 18 months as they get accustomed to the information search behaviour in the e-learning context and this is evidenced by an accuracy rate of 98.4% in situation C as shown in Figure 5.

In terms of the implicit parameters that have an effect on students' explicit relevance feedback after 18 months of the pandemic, Dwell time was the most important parameter that has a significant effect of 64.3%. in Figure 6, DT is positively correlated with students' academic search behaviour in either low or high relevance.

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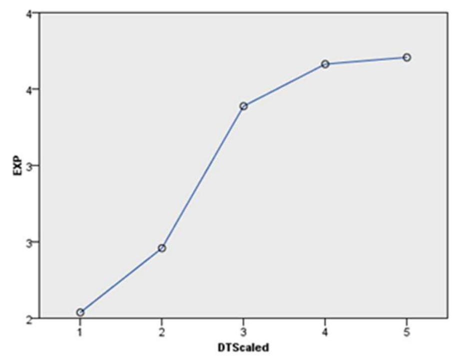

Figure 6 DT Scaled after the pandemic

Regarding mouse scrolling count which comes second in terms of importance (16.7%), one can see from Figure 7 that the predictive strength of these implicit indicators on web documents was positively correlated with students' search with low explicit relevance (1,2) and high relevance (3,4). This could be attributed to the fact that students can better assess the relevance of the document searched and increased mouse scroll denotes to their interest in the academic material found. One point to bear in mind is that the shift in the line (inverse relationship) for documents with low to moderate relevance indicates that stress might not have affected students' search behaviour after the pandemic due to confidence and experience gained by students.

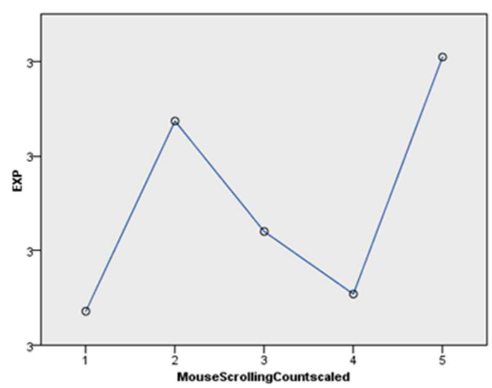

Figure 7 Mouse Scrolling Count after the Pandemic

In addition, data analysis reveals that mouse movement was a significant implicit predictor of students search behaviour in the after Covid-19 phase with an importance rate of around 4% as can be shown in Table 8. Also, mouse movement was present in the preceding two stages of this study (i.e. pre, during COVID-19 pandemic). Figure 9 demonstrates the positive relationship between mouse movement count and students' explicit relevance feedback, which indicates that as students get interested and find out the academic material searched is relevant they used to intensify the mouse movement. Vice versa when they perceive the document is irrelevant they used to reduce mouse movement. This trend after the COVID-19 pandemic could be explained that stress and anxiety experienced by students before and during the pandemic (i.e. stage 1 and stage 2 of the study) is no more affecting students search as a result of cumulative enhanced information-based web search skills and reinforced confidence.

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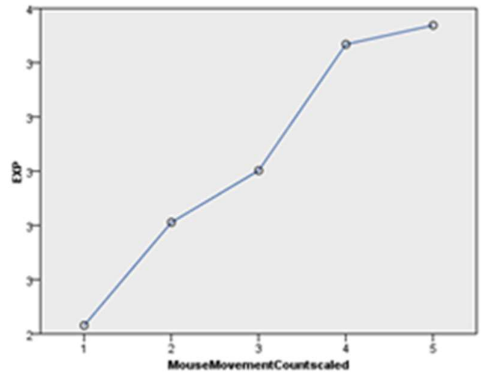

Figure 8 Predictive parameter “Mouse movement count” after the Pandemic

Furthermore, regarding the implicit predictor Copy, one can notice from Figure 9 that students used to copy the requested academic material, which were assessed as highly relevant and ignored copying the material that was poorly relevant or irrelevant.

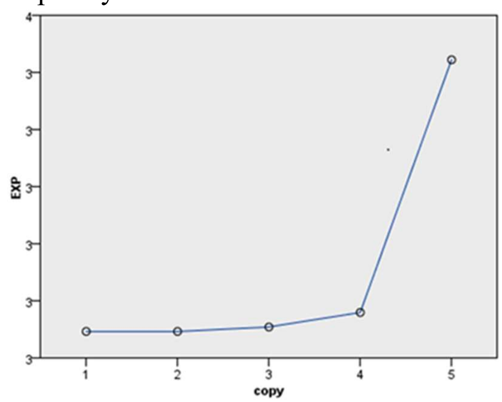

Figure 9 Predictive parameter “Copy” after the Pandemic

Additionally, mouse click count continues to be a significant implicit predictor in this study as we used to see in stage one and stage two of this study.

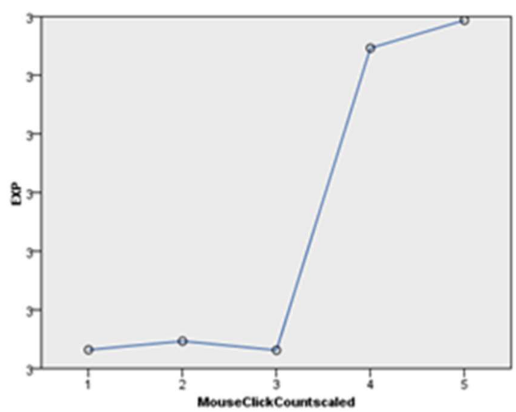

Figure 10 Predictive parameter “Mouse click count” after the Pandemic

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The line depicted in Figure 10 shows a steep and sharp increase, which denotes a positive correlation between documents perceived as strongly relevant and mouse clicks, whereas a few mouse clicks counted for documents that were not relevant from students' perspective. This shows that after the pandemic (post stage) students get used to better search and spot the most relevant web documents with no space for anxiety or stress due to students' familiarisation to the new e-learning setting where online assignments and task-based grading took place. This new situation after the pandemic necessitates students to be more active and trained on information based web search.

CONCLUSION

Studying the relationship between implicit and explicit feedback is crucial for building user-profiles and preferences. Explicit feedback is shown to be more accurate in indicating the interest level of the user. However, it is more difficult to collect as users tend not to provide their feedback explicitly. Consequently, studying the relationship between implicit and explicit feedback is important to develop accurate models to predict user interest from implicit feedback.

Covid-19, as a pandemic, imposed changes to user environments such as the stress and anxiety resulted from the health concerns, lockdowns, and social distancing. This paper investigated the changes in user search behaviour within the context of Covid-19. It attempted to identify the changes in the relationship between implicit relevance feedback parameters and the explicit feedback between pre-Covid-19 pandemic, during and after the pandemic.

The paper concluded that there are significant changes in the user search behaviour in the context of Covid-19 as the common implicit feedback parameters that are shown to have a significant relationship with the user interest level included only three parameters (Dwell Time, Mouse Scrolling Count, and Mouse Movement Count) in the pre pandemic study. Whereas, during the pandemic, two new parameters were shown to have a significant relationship with the interest level, which were Page Up /Down and Mouse Click Count. This can be attributed to stress, anxiety, and distance learning associated with the pandemic. Whereas after the pandemic (i.e. the post stage) only one implicit parameter-Copy- was added to the previous implicit predictors that significantly affected students explicit relevance feedback during the pandemic. All the significant implicit parameters had a positive relationship with the user interest level except Page Up /Down that was shown to have an inverse relationship. This could be also explained in the context of the pandemic as the stress level might make the user have less patience in finding the right information and consequently to use a faster way to skim the document, in particular, those document they start believing that they are irrelevant. The importance of the implicit feedback parameters also changed between situations A and B. for instance, the importance of the Dell Time decreased from 0.546 to 0.423. Furthermore, the importance of the Mouse Scrolling Count decreased from 0.352 to 0.067 affected by the entrance of the Mouse Click Count with relatively high importance of 0.315. the pace of change continued even after the pandemic where mouse scrolling increased to around 0.17 and the entrance of new implicit parameter which was Copy that came the last in terms of the importance compared to the other implicit parameters.

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