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RESEARCH PAPER

Enhancing E-Commerce Usability through Process Mining and User Behavior

Mostafa Karimi dehkordi[1], Sepideh Nasiri[2*]

[1] *M.Sc., Department of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran.*
[2] *Assistant Professor, Department of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran.*

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Abstract

E-commerce plays a vital role in today's economy, and website usability is crucial for attracting customers and achieving higher conversion rates. Process mining offers significant advantages in analyzing user behavior, providing insights into typical user paths and identifying deviations. This study aims to enhance the usability of e-commerce websites by leveraging user behavioral data and process mining tools. User behavioral data from a cosmetics e-commerce website were collected and preprocessed. Various metrics were established to evaluate usability, revealing low task completion rates and high bounce rates. Bottlenecks were identified where users faced delays, indicating areas for improvement. Recommendations included redirecting users who remove items from their cart to the homepage, suggesting similar products, and addressing payment page issues. These suggestions aim to improve user experience and increase conversion rates. Despite limitations, such as the lack of detailed data, this study demonstrates the potential of process mining tools in enhancing website usability.

Keywords:
E-commerce, Process Mining, Website Usability, Online Behavioral Data, Online User Behavior.

Introduction

The global economy is experiencing a significant transformation. The internet has greatly expanded the range of business activities. The amount of business information available through the World Wide Web is growing exponentially. This trend makes it easier to gather and analyze customer information and various business segments. As a result, information-based virtual value chains have become exceptionally important from both operational and strategic perspectives [1]. E-commerce as a way in changing marketing strategies through new technologies has played a key role in facilitating business operations and improving managerial decision-making. Studies indicate that e-commerce is a vital component of the modern economy with its volume reaching $6.3 trillion in 2023 and experiencing an annual growth rate of 10% [2].

In the information age, marketing managers require more data than ever to better understand customer needs and choose suitable marketing strategies that align with consumer expectations [3,4]. The substantial increase in data volume has caused organizations to depend on data analysis and extensive research to understand customer behavior [1]. Furthermore, given that user experience on electronic platforms directly affects e-commerce success, focusing on

* Corresponding author: (Sepideh Nasiri)
Email: nasiri@kntu.ac.ir.

enhancing the usability of e-commerce platforms is crucial [5].

In usability evaluation, quantitative and qualitative data are gathered through questionnaires and controlled observation methods. These methods are occasionally supplemented with techniques like eye tracking, think-aloud methods and interviews [6]. A significant source that is less utilized in traditional methods is the online data recorded from user behavior on digital platforms which should be more prominently considered with the expansion of online platforms. Process mining is one area that can utilize this user behavior data to enhance business processes and ultimately develop e-commerce.

Process mining is a research domain focused on discovering, monitoring and improving real-world processes by extracting data from event logs that are easily reachable in today’s information systems [7]. While process mining has been applied primarily in fields like healthcare and IT, its application for improving usability has been less explored than other uses [8]. Modern organizational information systems track detailed traces of business processes, and process mining methods help analysts understand the real performance and effectiveness of organizational processes by analyzing sets of data known as event logs [9].

This study aims to offer a concise and comprehensive review of methods for measuring and improving usability and analyzes various tools as effective approaches to enhance the quality and efficiency of e-commerce websites. It presents and evaluates process mining as an innovative and effective tool for analyzing online data. The primary innovation of this research is the use of process mining as a means to improve website usability and analyze online data. Focusing on the potential of process mining in this area, this study is among the first to explore this field. Furthermore, process mining tools will be employed to improve the quality and performance of commercial websites and practical recommendations for boosting usability and refining marketing strategies will be provided to the website managers studied. This research can benefit and be applied by all managers in the e-commerce sector, especially digital marketing managers. These actions could lead to a better user experience and increased success for businesses on digital platform.

Literature Review and Background

Usability and Measurement Methods

Usability, as defined by ISO 9241-11, refers to how well a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specific usage context. Nielsen defines usability as the ease of use and adaptability of a system for a particular user group who is expected to perform specific tasks in a specific environment [10]. Usability is traditionally characterized by five components: learnability, efficiency, memorability, error prevention and satisfaction. Measuring and improving usability focuses on assessing and enhancing these indicators [11].

Learnability is an important aspect of usability that should be considered when designing any software system [12]. It refers to how easily a user can understand how to carry out a task within the system on their first encounter [11]. According to ISO/IEC 25010, efficiency is one factor used to measure usability [13]. ISO 9241-11 defines efficiency as the resources expended concerning the accuracy and proportion of goals that users achieve [14].

Memorability is one of the most commonly cited usability components in various studies [15]. Nielsen defines memorability as follows: systems should be easily memorable and allow users to return to the system after a period of absence without needing to relearn everything [11,16]. In the error prevention system, there should be a low error rate and it should allow users to make few mistakes while using the system and enable easy recovery from any errors that do occur [11,16]. Moreover, catastrophic errors should be avoided. According to Nielsen's ten factors, the system should also provide a tool to prevent users from carrying out unintended actions [17].

Satisfaction is one of the three core components defined in ISO 9241-11's usability definition. This standard defines satisfaction as the degree to which the user's physical, cognitive and emotional responses resulting from using a system, product or service meet their needs and expectations. In other words, the system should be enjoyable to use and provides users with mental satisfaction during its use [11,16].

Regarding usability measurement methods, controlled observation and surveys are two primary approaches used in usability evaluation [6]. In observational methods, researchers watch users' behavior without interacting with them. Instead, selected users follow a set of instructions in a laboratory. Observation allows researchers to see participants' body language and facial expressions. This category includes methods such as heuristic evaluation, cognitive walkthroughs, semi-structured interviews, and think-aloud protocols [18]. Among the various methods, surveys are the most prevalent with questionnaires being the fundamental tool. Questionnaires are used to collect data from a sample of participants as representatives of the target population [6]. Methods such as the system usability scale, usability index for user experience, the unified theory of acceptance and use of technology fall into this second category [18].

Given the rapid expansion of the e-commerce market's value and scope and the vast amount of recorded online data, it is crucial to seek innovative methods for analyzing and improving the qualitative indicators of e-commerce platforms. Traditional methods for data collection and analysis face limitations such as high costs, long timeframes for accessing data and a small volume of data that can be examined. In contrast, using online data offers significant benefits including reduced data acquisition costs, shorter information retrieval times and increased volume and accuracy of data analysis. Therefore, to evaluate indicators like usability, it is essential to focus on modern tools and methods based on data mining that can utilize online data. In this context, one of the innovative and efficient tools is process mining which will be briefly reviewed next.

Process Mining

Process mining is a relatively new research discipline that bridges machine learning and data mining with process modeling and analysis [7]. The primary goal of process mining is to enhance operational processes through the systematic use of event logs. By combining event logs with process models, process mining techniques offer insights, identify bottlenecks and deviations, predict and diagnose performance and compliance issues and support the automation or removal of repetitive tasks [19]. In summary, process mining focuses on discovering, examining and improving real business processes using the event logs present in systems [20].

Van der Aalst has categorized the process mining stages into three main phases: discovery, conformance checking and process enhancement [20]. In process discovery, an event log, usually presented as an XES file, is mapped onto a process model such that the resulting model reflects the behavior observed in the event log [7]. The output of this phase can be represented in various ways such as Petri nets, Business Process Model and Notation (BPMN) or process trees. While discovery and transparency of processes do not immediately generate business value, they can provide value when combined with human analysis to identify and leverage improvements for the process [19].

Conformance Checking compares the events in the event log with those in the process model [7]. The purpose of conformance checking is to identify discrepancies between the actual log and the extracted process model [19]. Conformance checking requires an event log and a process model as inputs [21]. The techniques for conformance checking offer mechanisms to relate modeled behavior with observed behavior. Thus, the differences between the residual footprint of the actual process execution and the process models that provide the expected behavior become evident [22].

Process Enhancement refers to the development or improvement of an existing process model utilizing information derived from the real process as recorded in the event log [20]. This definition is the most frequently referenced in academic research in this domain [23].

Several software tools have been developed for process mining. One of the oldest is the ProM software which is well-regarded among researchers and experts in the field. Disco is a process mining tool available under a commercial license. It is simpler than ProM and is better suited for users with business expertise who may not have an academic background in process mining. Celonis is also a growing process mining platform. This product offers a powerful dashboard-based software with features for visualization and analysis and allows users to explore processes from various angles. Celonis targets medium and large enterprises [24].

Functional Potential of Process Mining in Improving Usability of Commercial Websites

Process mining tools and software can receive data related to the processes users go through on a website. After performing the discovery phase and arriving at an initial process model, these tools can display information such as the average time users spend on each activity within the process, the success rate of users in completing each activity and the percentage of users exiting the process at various stages. Following the conformance checking phase, the cited information becomes more precise where the accuracy of the process model is improved. Hence, it is recommended to first perform both the discovery and conformance checking phases before extracting the required information from process mining software.

Based on research, each of Nielsen's five usability metrics can be further broken down into additional criteria to clarify and improve their measurement. These criteria can be assessed using data available from process mining. For example, the learnability metric can be evaluated using criteria such as task completion rate, success rate and bounce rate. The task completion rate is defined as the percentage of activities completed successfully relative to the total number of activities attempted. The success rate represents the percentage of successfully completed activities compared to the total number of activities performed by the user. The bounce rate is defined as the percentage of visits where only one page was viewed and no other pages on the website were visited relative to the total number of visits [25]. Similarly, efficiency can be measured using criteria such as activity time, click rate and time on page; memorability can be assessed with the exit rate; error prevention can be measured by the error rate; and satisfaction can be evaluated using the conversion rate. A list of measurable usability metrics based on process mining and their calculation methods is provided in Table 1.

Methodology

This research aims to improve the usability of commercial websites by utilizing user behavior data from online platforms and leveraging the capabilities of process mining tools. The procedures followed in this study are based on the framework shown in Fig. 1.

Initially, after selecting a suitable database, we carried out data preprocessing. Data preprocessing is a vital step to ensure the accuracy and reliability of subsequent analyses. The data for this study was obtained from the Kaggle database and includes a dataset of user behavior on an e-commerce site for cosmetics from December 2019. This dataset features a detailed event log from an online cosmetics store which includes user IDs, timestamps and types of events (user interactions) such as page visits (view), adding items to the cart (cart), removing items from the cart (remove from cart) and completing purchases (purchase). After removing any duplicate or incomplete records, the data can be analyzed using process mining tools.The preprocessed data is then imported into process mining tools and after executing the discovery and conformance checking phases user behavior maps are generated. This stage is carried out using all three process mining software tools (ProM, Celonis and Disco) because of the relative advantages of each tool and the most comprehensive output is provided for analysis. The process models obtained provide a general view of the traces that users navigate through different pages of the website and identify deviations from expected logical traces.

Table 1. Usability Evaluation metrics based on process mining

Nielsen usability component	Metric		
Learnability	**Metric**	**Completion rate**	**Bounce rate**
	Formula	$\frac{\text{number of completed tasks}}{\text{total number of attempted tasks}}$	$\frac{\text{number of single} - \text{page visits}}{\text{total number of visits}}$
	In-app location	**ProM**: XES event log, **Celonis**: process explorer, **Disco**: map	**ProM**: XES event log, **Celonis**: process explorer, **Disco**: map
Efficiency	**Metric**	**Time on task**	**Time on page**
	Formula	total time spent on tasks	average time spent on a page
	In-app location	**ProM**: XES event log, **Celonis**: process explorer, **Disco**: map	**ProM**: XES event log, **Celonis**: process explorer, **Disco**: map
Memorability	**Metric**	**Exit rate**	
	Formula	$\frac{\text{number of exits from a page}}{\text{total number of visits to the page}}$	
	In-app location	**ProM**: XES event log, **Celonis**: process explorer, **Disco**: map	
Error	**Metric**	**Error rate**	
	Formula	$\frac{\text{number of errors}}{\text{total number of actions}}$	
	In-app location	**ProM**: XES event log, **Celonis**: process explorer, **Disco**: map	
Satisfaction	**Metric**	**Conversion rate**	
	Formula	$\frac{\text{number of conversions}}{\text{total number of visitors}}$	
	In-app location	**ProM**: XES event log, **Celonis**: process explorer, **Disco**: map	

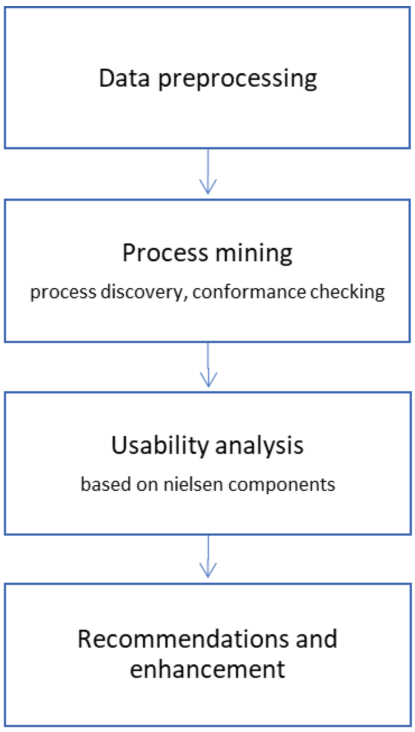

Figure 1. Methodology procedure

In the next phase, using the outputs from the previous stage (user behavior maps), the usability of the website is assessed based on Nielsen's usability metrics. These metrics can either describe the general movement trends of users on the website or include specific measurable criteria. At the end of this phase, some challenges and issues related to the website's usability are identified. Finally, based on the analyses conducted in the previous stages, recommendations are made to improve the website's usability. These recommendations may include changes in user interface design, improvements in navigation traces and reduction of complexities in user processes on the website.

Results

This section presents the results of the four stages outlined in the methodology section of the current study, including data preprocessing, user behavior modeling, usability analysis, and recommendations and improvements are presented.

In the data collection and preprocessing stage, user behavior data from the selected website was gathered and organized. The raw data consisted of user event logs which were transformed into a suitable format for process mining tools after removing duplicate and incomplete records. The final data set includes 184,629 events categorized into four groups: view, cart, remove from cart and purchase. Table 2 shows the user event logs. For example, in the first row, user with ID 576802932 viewed a product with ID 5904500 from brand Yoko. Additionally, based on the outputs obtained from the process discovery phase using ProM, 4,720 different traces were traversed by users across the website's pages.

Table 2. Sample data of the dataset

Event time	Event type	Product ID	Brand	User ID
2019-12-01 00:17:40 UTC	view	5904500	Yoko	576802932
2019-12-01 00:17:40 UTC	view	5904789	Entity	576802932
2019-12-01 00:17:41 UTC	cart	5699770	Ingarden	538507783
2019-12-01 00:17:48 UTC	cart	5845196	Masura	494077766
2019-12-01 00:17:48 UTC	remove_from_cart	5877610	Bpw.style	576802932
2019-12-01 00:17:49 UTC	remove_from_cart	5889907	Ingarden	576802932

Table 3 includes specifications of the dataset, including the frequency of traces, events, Event classes and variants.

Table 3. Specifications extracted from the dataset

Specifications	Results
Traces	44193
Events	184629
Event classes	4
Variants	4720

In the next stage, by importing user behavior data into process mining tools process models based on user behavior on the website are created as user behavior maps. These models provide an overall view of users' typical traces through the website and detail the activities performed by each user on different pages and the time spent on each activity. Additionally, since the available data is time-stamped it can display deviations from expected behavior. Fig. 2 shows the user behavior model within the Celonis software. As depicted in this image, various traces have been taken by users across the website, observable through the arrows connecting different activities. The chart below displays the average time spent by users on different activities. For example, users spent an average of 5 minutes viewing the cart page before proceeding to the checkout page. It is also possible to display the same chart based on metrics such as the number of cases, median time spent, etc. It is important to note that all these reports are considerable for evaluating the usability of the respective pages by managers and experts in this field.

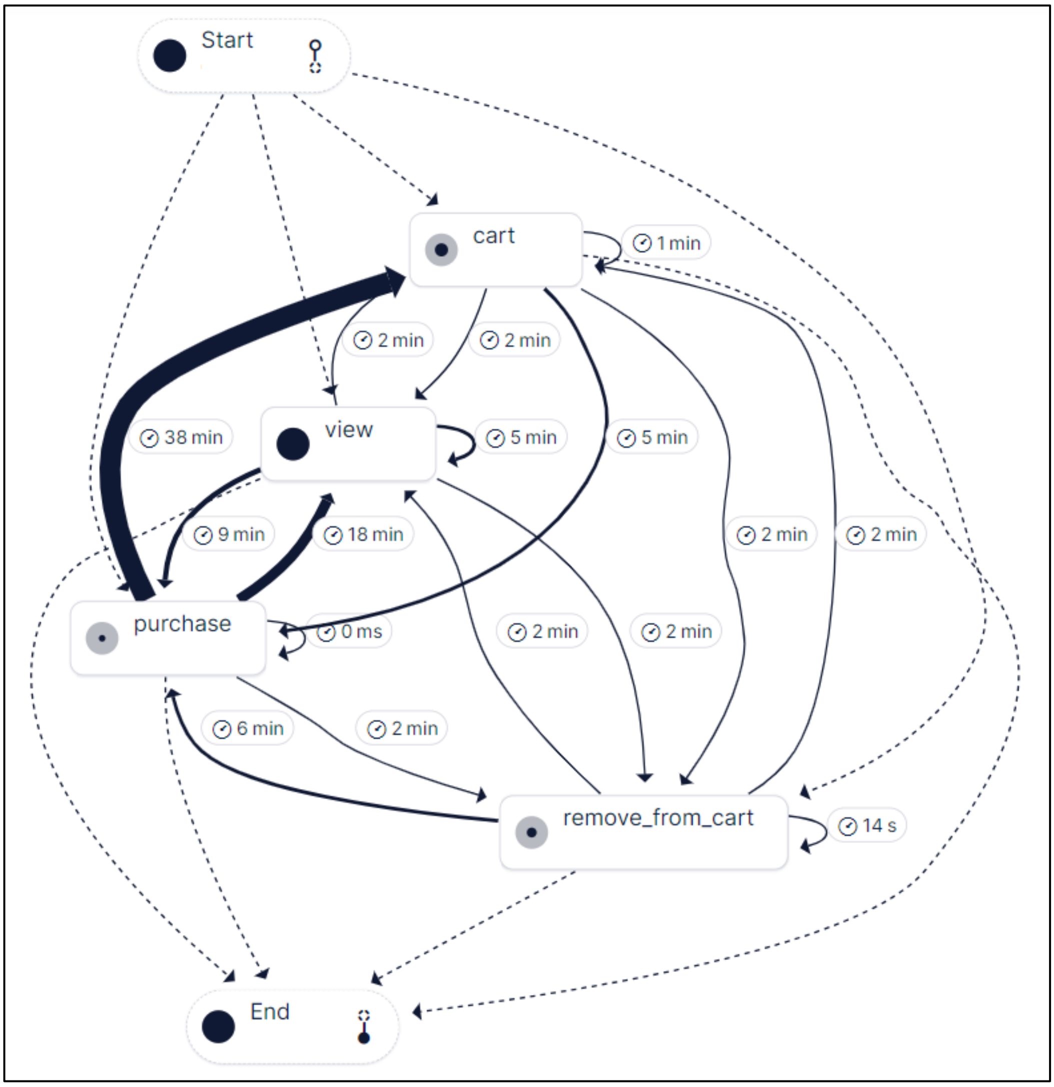

Figure 2. Extracted behavioral maps of users in Celonis software

In fig. 3, the results of examining the types of activities performed are displayed in the ProM software based on the frequency of each activity and the percentage of each activity relative to the total activities. Additionally, this figure shows the number and percentage of start and end activities. For instance, it is possible to determine how many and what percentage of users began their visit to the website with a viewing activity and how many and what percentage of them concluded their last activity on the website with completing the purchase. Based on this output, approximately 47% of the activities were views, 27% were cart-related, 19% involved removing items from the cart and around 6% were purchases. Furthermore, about 89% of user behavior traces started with a viewing activity, 7% with cart-related actions, 3% with item removal, and less than 1% with a purchase. Finally, approximately 84% of the traces ended with a viewing activity, 9% with cart-related actions, 4% with item removal and 3% with a purchase.

In the final step, based on the outputs obtained from the previous stages, the usability status of the website is reviewed using Nielsen's usability criteria. The process-mining-based usability improvement methodology is applied and potential usability challenges related to the website are identified. Recommendations for enhancing usability are also provided.

Event Name

Event classes defined by Event Name

All events

Total number of classes: **4**

Class	Occurrences (absolute)	Occurrences (relative)
view	87085	47.184%
cart	49323	26.724%
remove_from_cart	36814	19.946%
purchase	11344	6.146%

Start events

Total number of classes: **4**

Class	Occurrences (absolute)	Occurrences (relative)
view	39430	89.259%
cart	3263	7.387%
remove_from_cart	1343	3.04%
purchase	139	0.315%

End events

Total number of classes: **4**

Class	Occurrences (absolute)	Occurrences (relative)
view	36984	83.722%
cart	4125	9.338%
remove_from_cart	1831	4.145%
purchase	1235	2.796%

Figure 3. The frequency of activities performed by users

Table 4 displays the results of calculating quantitative usability metrics which is categorized by Nielsen’s usability criteria and for each activity performed on the website. Various metrics such as task completion rate, bounce rate, activity duration, efficiency, exit rate and error rate are analyzed in this table.

The activity completion rate represents the percentage of completed activities compared to the total activities. Considering that the purpose of users entering the website is not precisely known, in the calculation of the completion rate, it is assumed that the purpose of all users entering the website was to make a purchase. With this assumption, the completion rate obtained is equal to 2.6%, which is a low rate. Of course, it should be kept in mind that there are users who have entered the website with other purposes than making purchases. Therefore, in order to more accurately calculate the completion rate, it should be possible to identify the purpose of users entering the website using various methods such as online and offline surveys.

Bounce rate indicates the percentage of users who leave a website by viewing only one page. According to Table 4, the bounce rate of the viewing stage is equal to 48.12%, in the cart stage it is equal to 12.62%, and in the stages of removal from the cart and purchase, it is insignificant. The high bounce rate indicates that many users quickly leave the website after entering which could be due to unattractive content or weakness of website advertising in other platforms.

The activity duration (time on task) of users is also examined in this table. This metric shows the average amount of time that users spend on each page. According to Table 4, on average, users spent about 24 minutes for the viewing activity, about 11 minutes for the cart activity, about 9 minutes for the cart removal activity, and about 46 seconds for the purchase activity. This information can assist website managers in identifying pages with high activity durations and making the necessary improvements.

The time spent on pages is also a significant metric in this table. It reflects how much time users spend on various website pages and whether this time is optimized. The difference between this metric and the activity duration is that the activity duration can include the time of execution of a command such as deleting from the cart by users until it is done on the website, which indicates the speed of executing various commands on the website. In the calculation of spent time, due to the lack of sufficient data such as data indicating the page of each activity, it is not possible to accurately calculate this measure. For this reason, the time spent on the page is considered equal to the activity duration. It is worth noting that since the activities of the cart and removal from the cart are both related to the cart of the employees, they are added together and presented as one number in the measure of time on the page.

The exit rate of each page indicates the number of users who leave the website after entering that specific page, without performing any actions. According to Table 4, the exit rate from viewing stage is 82.8%, from the cart stage is 8.6%, and from the remove from cart and purchase stages is 4.2%. This again shows the high percentage of users who leave the website after viewing one or more pages of the website without taking any other action. This could be due to problems in the design or content of the website that need to be reviewed and improved.

Additionally, the error rate is an important metric in this table. It shows the number of errors that users encounter while navigating the website. This data can help website managers identify technical and usability problems and implement necessary changes. By offering details, this table helps to more accurate and comprehensive analysis of the data and also aids website managers in enhancing usability and boosting user satisfaction. In calculating, due to the lack of sufficient data, it is not possible to accurately calculate the error rate. For this reason, this metric is calculated only at the purchase stage, assuming the existence of errors in consecutive purchases, and the result is equal to the rate of 2.6%.

Table 4. usability metrics' evaluation results

Nielsen usability component	**Metric**	**Score**			
		View	Cart	Remove from cart	Purchase
Learnability	Completion rate	2.6 %			
	Bounce rate	48.12 %	12.62 %	0.006 %	0.000 %
Efficiency	Time on task	24.09 min	10.64 min	8.92 min	46.15 sec
	Time on page	24.09 min	19.56 min		46.15 sec
Memorability	Exit rate	82.8 %	8.6 %	4.2 %	4.2 %
Error	Error rate	Lack of access to relevant data	Lack of access to relevant data	Lack of access to relevant data	2.6 %
Satisfaction	Conversion rate	Lack of access to relevant data			

In next step, some behavioral patterns in the user data that did not align with the expected behavior of users on commercial websites were examined in order to identify potential issues with the website. One such case is users whose first activity on the website was removing an item from the cart. This behavioral pattern could have several causes. One possible reason might be incomplete extraction of user behavioral data from the website's database. This means that some records were not retrieved. Another reason could be that the user left some activities unfinished during previous visits to the website. According to the calculations presented in Table 4, this occurrence happened 1,343 times on the website which is equivalent to 3.04% of all user traces. Moreover, of these occurrences, 161 traces finally led to a purchase which represents 11.98% of the traces that began with a "remove from cart" action and 0.03% of all user traces on the website. On the other hand, 1,182 traces that started with a "remove from cart" action did not result in a purchase which represents 88.01% of these traces and 0.26% of all user traces. It seems that in order to improve the usability of the website, users who enter the remove from cart stage in their first action on the website can be automatically transferred to the first page of the website. Additionally, actions such as suggesting similar products after an item is removed from the cart could increase the likelihood that these users' activities on the website will finally lead to a purchase. The information related to this category of traces including their count, relative frequency percentage and overall frequency percentage is shown in Table 5.

Table 5. Statistics related to the traces which started by remove from cart

Trace's feature	Frequency	Relative abundance percentage	Percentage of total frequency
Every trace which started by remove from cart	1343	100 %	3.04 %
Traces which started by remove from cart and led to a purchase	161	11.98 %	0.03 %
Traces which started by remove from cart and didn't led to a purchase	1182	88.01 %	0.26 %

Traces that involve consecutive purchase steps are worth investigating. As expected, based on the logical behavior pattern of commercial websites, if the purchase step is completed correctly, there should be no need to repeat this action. In fact, after completing a purchase, users either leave the website or navigate to other pages besides the purchase page. The presence of consecutive purchases in the recorded behavioral patterns of website users could indicate issues such as malfunctioning purchase page links, problems with the purchase gateways connected to the page or unclear images containing security codes. Based on the calculations presented in Table 6, 88.3% of all traces that involved a purchase had two or more consecutive purchase actions without any gap. This statistic indicates significant and recurring issues on the purchase page and to resolve them the potential causes mentioned must be thoroughly investigated and fixing these issues should be prioritized.

This table also provides data on the total number of traces that include the purchase step which makes them observable and examinable. Out of all the traces taken on the website, 1,322 contain the purchase step which constitutes 2.9% of all traces. Thus, if we assume that completed activities are those that have reached the purchase step, the task completion rate on the website can be considered equivalent to this 2.9% which is not a high percentage. Hence, in addition to the mentioned issues, attention must also be paid to the fact that around 98% of website visitors finally leave without making a purchase. Likely reasons for this might include incorrect selection of advertising platforms and marketing communications, an unclear purchasing trace, out-of-stock products, higher prices than similar websites and the website's slow speed. Nevertheless, as mentioned before, if we have access to the data related to the purpose of users to enter the website, we can have a more comprehensive analysis regarding the above indicators.

Table 6. Statistics related to the traces which include purchase

Trace's feature	Frequency	Relative abundance percentage	Percentage of total frequency
Traces which include purchase	1322	100 %	2.9 %
Traces which include consecutive purchases	1168	88.3 %	2.6 %
Traces which don't include consecutive purchases	154	11.6%	0.3 %

Traces in which no activity other than viewing products occurred can be considered as potential customers. Analyzing these traces is somewhat similar to analyzing those traces where no purchase activity took place. As shown in Table 7, 42.9% of the traces taken on the website by various users only include viewing different pages with no activities such as adding a product to the cart, removing it from the cart or making a purchase and it is necessary to carry out targeted marketing communication programs for these potential customers.

Table 7. Statistics related to the traces which include view step

Trace's feature	Frequency	Relative abundance percentage	Percentage of total frequency
All traces which include view step	25617	100	57.9
Traces which only include view step	18993	74.1	42.9

Conclusion

This study aimed to enhance the usability of e-commerce websites by analyzing user behavior data with process mining tools. E-commerce, a vital component of the modern economy, depends heavily on user experience to attract customers and achieve higher conversion rates. Given the intense competition in this field, optimizing website usability has become increasingly crucial for business success.

To achieve this, we explored the use of process mining tools as a novel and effective approach for analyzing and improving the usability of commercial websites. By extracting process models from user behavior data, these tools provide a detailed view of typical user paths and deviations from expected behavior, helping website managers identify both strengths and weaknesses in their website's design and functionality.

Using data from an e-commerce website specializing in cosmetics, we employed process mining techniques to analyze key usability metrics, including task completion rate, bounce rate, and exit rate, based on Nielsen's usability criteria. Our analysis revealed several areas for improvement, such as high bounce rates and low task completion rates, indicating usability challenges that need to be addressed.

Based on these findings, we proposed actionable recommendations to enhance the website's usability. These include revising promotional strategies, automatically redirecting users who first engage in cart removal to the homepage, suggesting alternative products when items are removed from the cart, and resolving issues with the purchase page to minimize user frustration and improve conversion rates. Implementing these strategies could significantly enhance user experience and satisfaction.

While this study provides valuable insights, it also has limitations, including the lack of access to more detailed data, such as user intent and satisfaction levels. Future research should focus on collecting more comprehensive data, including the success or failure of specific actions and user feedback, to allow for a more in-depth analysis of usability issues.

Overall, this research demonstrates the potential of process mining tools in identifying and addressing usability problems on e-commerce websites. By leveraging user behavior data, website managers and digital marketers can gain a deeper understanding of user needs and behaviors, ultimately leading to improved website performance and higher user satisfaction.

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