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IMPROVING USER EXPERIENCE IN E-COMMERCE BY APPLICATION OF PROCESS MINING TECHNIQUES

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Abstract: Nowadays, a lot of attention in e-commerce is paid to improving user experience. Due to a high competition on the market, e-commerce websites must provide services focusing on usability and quality of service. For this purpose they can detect possible problems by using data which represents customer behavior while navigating the website, described by the sequence of actions performed by a customer on the portal. The goal of this article is to propose an approach to apply process mining techniques for mining website logs, to discover user paths and patterns often seen in a website. Patterns retrieved from user's most frequent browsing behavior are then utilized to analyze usability issues. The paper presents a general model for improving an e-commerce website based on the application of process mining techniques. The findings of the article showcase that it is possible to analyze and improve a website based on results achieved by applying process mining techniques on the web logs the site produces. The usefulness of provided model is proven on logs from a Polish e-commerce portal.

Keywords: web mining, process mining, user experience, usability, e-commerce

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Introduction

E-commerce market is growing in sales, volume and variety of data generated. Retail ecommerce sales achieved 2 290 trillion USD worldwide in 2017 (Emarketer 2017) and about 40 billion Polish zloty (PLN) in Poland (Gemius 2017). This dynamic environment is highly competitive and provided services must be of high quality (Dadashnia et al. 2016, p. 1665, p. 1673) and usability (Distante et al. 2014, pp. 497-501). Based on the concept of knowledge based economy in management studies (Olszak 2007, pp. 17-44), the companies need to utilize the wealth of information available to them to improve their services and internal processes. They also need to utilize IT tools which allow to process information into business applicable knowledge that can give them competitive advantage. Website owners can utilize user data collected passively from their clients' interaction with the website (Brown, Chui, Manyika 2011, p. 7). Utilizing user produced data results in a less contrived and methodologically biased information about customer behavior, than information collected by standard surveys (Müller et al. 2016, p. 292). Streams

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of log data are also a valuable source for customer purchase prediction, better than any demographic data (Raphaeli, Goldstein, Fink 2017, p. 3). The current analytical approaches however, focus either on tracing the click stream and deriving the rate of conversion, or static analysis of a user profile. We would like to address this deficiency by focusing on the interaction of users with the website.

The goal of the paper is to is to propose a model for improving usability of the website taking into account dynamic aspects of user's activity on the portal. The methodology behind the research follows the principles of the Design Science (Hevner et al. 2004, pp. 75-100).

The paper is structured as follows: after an analysis of the literature (related work) in the next section, the problem is formulated, together with suggestions to tackle this problem and answer research questions. Next, the current state of this research is described by focusing on the use case validation of the proposed model. The paper conclusions are described in the Summary.

Related Work

Analysis of website user activity log data, may answer a number of different questions connected with demographics of customers or their frequent behavior (Astromskis, Janes, Mairegger 2015, pp. 139-140). The website logs are a source of knowledge for any e-commerce company and can be created from different data sources with varying aggregation levels (such as clickstreams, interaction with UI (User Interface) elements, paths of traversing the webpage and sequences of actions, etc.). Those logs are connected with existing purchase business processes. Applying process mining to these interaction patterns allows analyzing importance and flow of processes. Utilizing more detailed data allows companies to obtain information about the events surrounding the main business processes in the system. In case of websites, such a process-based website analysis is called web mining (Shen, Wang 2010, p. 337). The goal is to extract the knowledge from web data by application of data and text mining techniques. Similarities between process and web mining include also similar goals - results of analysis can be used for: prediction (e.g. likelihood of a purchase (Raphaeli, Goldstein, Fink 2017, p. 9) or rate of conversion), website optimization and usability improvement (Gkantouna, Tsakalidis, Tzimas 2016, p. 219), refactoring of processes (Distante et al. 2014, p. 503), personalization (Dadashnia et al. 2016, pp. 1669-1670), recommendation, user classification and clustering (Dias, Ferreira 2017, p. 300), security or load balancing.

The data for Web usage mining comes from a limited number of sources, however they may have different aggregation levels, which can provide various insights. The data types used include: clickstream data, website logs, Document Object Model/ Graphical User Interface elements interaction logs, user input: mouse cursor position and hovering time over a specific UI object, phrases written into search and text inputs, process logs (mostly software based defined events).

An analysis of mined website logs may provide information about the quality of service provided in terms of usability. Usability is "the degree to which a product or system can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use" (ISO 25010, 2011). If we understand the process of user interaction as broadly as from the moment the user visits the site, through his/her browsing behavior, until the decision of purchasing products - we can employ various methods for improving the user experience connected with the provided e-commerce service and the underlying process. Table 1 presents recent approaches to improving the usability of a website and processes of user interaction based on various sources of data. There is also an issue of measuring effects of implemented improvements. Possible metrics (which do not require expert knowledge) may include: change in time required to perform actions, average number of actions to carry out transactions (Geng, Tian 2015, p. 91), number of observed anomalies and detected usability issues/events (Grigera et al. 2017, pp. 132-134), conversion and bounce rates (or similar metrics) (Dias, Ferreira 2017, p. 298) or satisfaction level expressed by users. These metrics may also be applied in case of the proposed model. This list however should be further extended taking into account goals and KPIs (Key Performance Indicators) of the organization.

Table 1. Approaches for improvement of a user experience of a website

Publications	Source of data	Approach	Proposed or achieved goals
(Rubin et al. 2014 p. 57; Astromskis, Janes, Mairegger 2015, pp. 137-141)	Software interaction logs (actions).	Standard process mining (Disco).	Identified number of steps needed to carry out main processes in the system, also frequent and rare process paths and activities. Can be used for refactoring processes.
(Dadashnia et al. 2016, pp. 1663-1673)	Processed clickstream and server logs.	Web application built on SAP platform Prototype utilizing SAP HANA in memory database. Exact methods not stated.	Basic metrics. Generating personalized UI elements and shortcuts. Predicting next action - page preloading. Automatically simplifying the design by removing/hiding the unused and unnecessary elements - functionality overhead.
(Dias, Ferreira 2017, pp. 297-304)	Web mining per webpage. Specific data model with pages and user sessions.	System utilizing specific data model tested on e-commerce datasets. Metrics derived based on statistics from the data in the model.	Basic Metrics (bounce rates, conversion, click-through, customer retention, shopping cart abandonment). Mining user preferences for visited pages, clustering users into groups with different characteristics of above metrics.

(Distante et al. 2014, pp. 497-529)	Business process models.	Analyzing business processes and providing re-factored versions after manual change of underlying processes.	Web Business Process Refactoring, encompassing actions such as: grouping, splitting, adding or removing activities, modifying control-flow, making activities optional, improving and clarifying navigation paths, explicitly showcasing process state by UI elements.
(Grigera et al. 2017, pp. 129-148)	Proposed preprocessed set of defined usability events showcasing patterns of user interaction with the site content.	Own system of detecting events employed on a website based on clickstream logs.	System, that based on user behavior can automatically identify usability issues with a certain accuracy – on average about 60% (false positives are present) compared to the manual testing. Some refactoring suggestions are present.
(Geng, Tian 2015, pp. 84-94)	Session and logging data. Sequences of visited pages are extracted based on start and end events. Utilizes XML based schemas.	Using trail-tree construction based on a model consisting of states and transitions and baseline IUIP models built by experts. Comparing the assumed sequence of actions with the actual logs.	Mostly focusing on problems connected with page navigation and expected duration of a visit (as well as time needed to perform actions). The outcome is used as a platform to inform usability experts and analysts on how user behavior differs from the baseline assumed interaction model. The authors propose validation metrics based on success rate of a performed task.

Source: Own study

In addition to approaches described above, a considerable number of Web analytics tools is offered to website owners. Typically these tools collect raw data about visitors and organize it in a way that is easier to examine and comprehend. Generally, a distinction between two types of programs may be observed. The first group, called “log analyzers”, uses server logs in order to present various insights about visitors’ behavior. The other group is called “analytics applications”. These tools collect information about Web activity and generate reports by using bits of code installed on a website. Top Web analytics tool - Google Analytics (63.13% of market share (Datanyze 2018)), besides providing basic reports, such as users’ origin, device of use, total page views or average session duration, provides website owners with the flow reports. Flow reports may be divided into several subcategories with the major focus on Behavior Flow report and Funnel/Goal Flow reports. The main objective of the Behavior Flow report is to provide insight of how users traverse and interact with a website. The Behavior Flow visualizes the path a user follows from one page or event to another (called an "interaction"), starting at a landing page

(Gabriel 2016). Funnel visualization provides information about all of the drop offs at each step in the funnel conversion, which may be further used for optimization. The standard Funnel Visualization graph may mask skipped steps by utilizing backfilling, and cannot represent loops, jumps or skips that may happen through steps, which are distinctly shown in Goal Flow report.

Model of analyzing usability of websites by application of process mining techniques

Due to the fact that custom (usability-oriented) analytical systems may be too costly and complex to be used effectively by website owners and developers, there is a need for providing more business oriented analytical tools. We propose to apply process mining to analysis of website logs, however focusing on improving the usability of the website. Our goal is to prove that process mining can provide insights in line with current Web analytics but also be used to detect usability issues and provide clear suggestions for the potential website improvements. The problem that is to be addressed in the paper concerns definition of steps and potential tool support to derive from process mining insights to improve website usability. We follow O. Raphaeli, A. Goldstein and L. Fink (Raphaeli, Goldstein, Fink 2017, p. 5) to define the model of the analysis process as depicted in *Figure 1*.

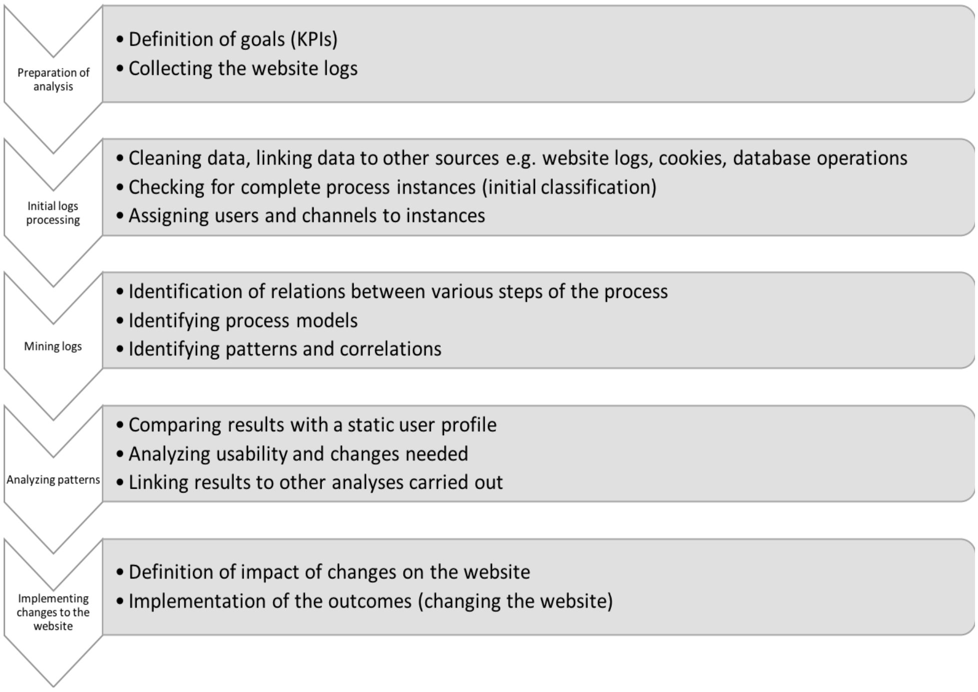

Figure 1. Proposed model for improving usability of websites by application of process mining techniques

Source: Own study

The proposed analytical process consists of five steps:

1. preparatory phase that aims at defining goals for the analysis and collecting data that will be used,
2. initial processing – dealing with data cleaning, data linking (logs from various sources) and indicating a link between a process instance (visit) and a user (visitor); the last step is to enable for aggregating results of the process based analyses with demographical/statistical data,
3. mining logs – concerning application of process mining techniques to analyzing website logs with the goal not only to describe processes, but also correlations and patterns that may be found,
4. analyzing results achieved in the process mining w.r.t. scope of changes needed to improve usability of a website usability as well as linking results of analysis with other analyses carried out,
5. implementing changes to the website to improve the user experience.

We assume that process logs available for analysis include all important information as suggested e.g. by (Dadashnia et al. 2016, pp. 1667-1669).

Validation of the model

This section presents validation of the proposed model using website logs generated by a Polish e-commerce website. Our goal is to utilize collected logs to provide insights which may be applied to increase the usability of a website following the steps provided in *Figure 1*. Firstly, some general remarks on e-commerce websites are given to emphasize applicability of results over multiple retailers. Secondly, the obtained logs are pre-processed to enable analysis using the ProM Framework (http://www.promtools.org/).

Leading e-commerce websites are all characterized by a similar design. All portals include search as the main part of the website, a part with an add (being subject to frequent changes) and the part with categories (for browsing). Only the Amazon website does not include categories listing on the main page. For simplification, in this study, we focus on a typical process performed by a user using a mobile application. The process includes the following steps:

– Checking the status of a profile/actions on “my Account” website.
– Searching for items.
– Displaying details of a specific item.
– Displaying contact details of a seller offering an item.

The log being subject to analysis consists of 1369 cases (process instances) with 76.975 events representing 21 classes. It may be easily noticed that the number of classes is limited, however an average number of actions per user visit (process instance) is quite high - 56,2 actions. Unfortunately, the average does not show us that there is a huge number of instances containing only few steps. The distribution of instances frequency is long tailed as the three events (displaying account details, browsing list of results and showing details of an item) constitute over 95% of all events in the log. Also, there are few instances which are very long and consist of a number of events - which point to the identification of various user groups with different browsing patterns. What should be noticed is that in some process instances, some actions appear more than once (without any action between them). This shows that a user clicked a couple of times on a certain button, before a requested content was displayed, which allows for an easy detection of the first usability-related issue.

The analysis covers a period from June to January, with instances equally distributed during this period. This was achieved by application of a sampling method, however the portal has also a stable interest during the year. In *Figure 2* it may be noticed that most of the cases have a duration of up to 3 hours. There is also a group of visits of about 11-12 hours long and only a few taking longer (up to one day), what usually means that the session within a browser was not closed. It might be however interesting that users use a portal not only for a single action (e.g. searching a specific category or looking for an item), but also similarly to the "news portal" searching for occasions. This should be an important conclusion for a software developer. Another analysis enables to present a process a user follows on the website. Such analysis should be used in addition to the funnel analysis usually applied. Our analysis shows cycles a user performs on the website while browsing. Together with an analysis of frequencies, it provides important information on how a user should be supported and what content is the most interesting to a user. When studying paths, it is important to focus on frequently visited paths as they represent the behavior of most of users.

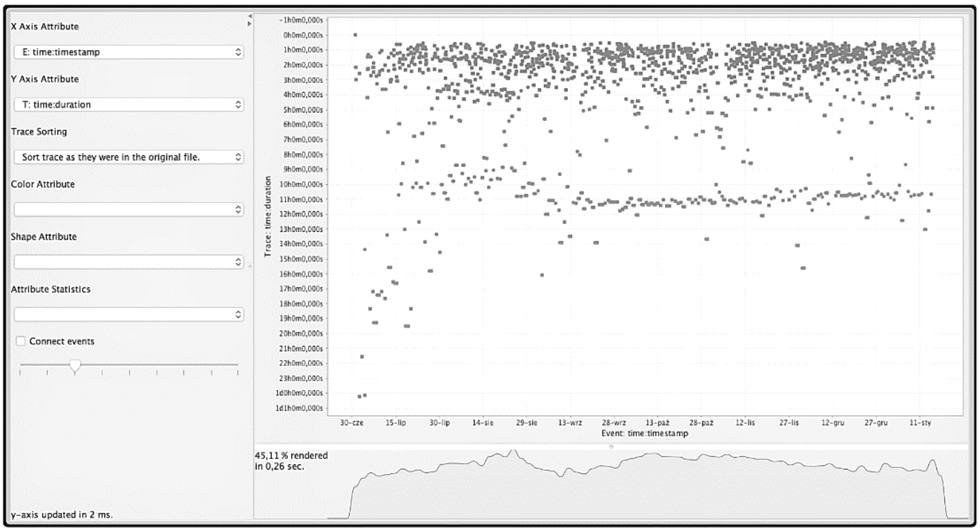

Figure 2. Duration of process instances (visits)

Source: Own study using ProM

Figure 3 presents exemplary paths that were found in our log. It should be noticed that in 1369 process instances, some of the patterns appear more often than once for a process instance. Such pattern as *myaccount-complete* should be addressed by a website developer in the first place (there are instances, where a user executes this step a couple of times one after another). This means that a user does not see that a website is opening or there are other problems concerning the situation.

Pattern Alphabet	Pattern Sequence Set	Alphabet Count	Instance Count (%)	Conservedness Metric
myaccount-complete	myaccount-complete	61438	99	100
item-complete	item-complete	3729	82	100
resultset-browse-list-complete	resultset-browse-list-complete	5814	78	100
item-complete resultset-browse-list-complete	resultset-browse-list-complete item-complete --- item-complete resultset-browse-list-complete ---	1997	62	32
item-complete replyform-complete	replyform-complete item-complete --- item-complete	1068	38	20

Figure 3. Most frequently detected patterns

Source: Own study using ProM

Another issue concerns user paths and events that go together. *Figure 4* presents a result achieved by application of Discover Matrix component from ProM. It shows relations between tasks. Darker value (originally blue, close to 1) indicates that there is a causal relation between two events in the process log, gray (originally red, close -1) indicates that no relation could be found. In case a website developer wanted a user to follow a certain path and no causal relation could be found, the applied solution is not successful. The correlated values suggest relations that may influence the future model of the website as a causal relation should be studied.

Causal Activity Matrix

Select visualisation ...

Matrix	contact_...	contact_...	contact_...	contactu...	editform...	home+c...	howitwor...	item+co...	landings...	login+co...	myaccou...	notfound...	payment...	payment...	postingf...	replyfor...	replysent...	resultset...	resultset...	resultset...	resultset...
contact_...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.5	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
contact ...	-1.0	-0.519...	-1.0	-1.0	-1.0	-1.0	-1.0	-0.521...	-1.0	-1.0	[illegible]	-1.0	-1.0	-1.0	-1.0	-0.4686...	0.5	-1.0	[illegible]	0.6666...	0.5
contact_...	0.5	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
contactu...	1.0	1.0	1.0	0.738...	1.0	1.0	1.0	1.0	1.0	1.0	0.4	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
editform...	-1.0	-1.0	-1.0	-1.0	-0.738...	-1.0	-1.0	0.2222...	-1.0	-1.0	-0.392...	-1.0	[illegible]	-1.0	-1.0	-1.0	-1.0	-1.0	[illegible]	-1.0	-1.0
home+c...	-1.0	-1.0	-1.0	-1.0	-1.0	0.0	-1.0	-0.25	-1.0	0.4	-0.568...	-1.0	-1.0	-1.0	0.5	-1.0	-1.0	-1.0	[illegible]	-1.0	-0.166...
howitwo...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.5	-1.0	-1.0	-1.0	-1.0	-1.0
item+co...	-1.0	[illegible]	0.5	[illegible]	-0.222...	0.25	-1.0	0.0	-1.0	0.5	-0.084...	-1.0	0.5625	-1.0	-0.671...	0.0716...	-0.222...	-1.0	-0.077...	-0.2962...	-0.033...
landings...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	-1.0	-1.0
login+co...	-1.0	-1.0	-1.0	-1.0	-1.0	-0.4	-1.0	-1.0	-1.0	0.0	0.1901...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-0.25	-1.0	-1.0
myaccou...	-1.0	-1.0	-1.0	-0.4	0.3978...	[illegible]	-1.0	0.0848...	-1.0	-0.1904...	0.0	-1.0	-0.518...	-1.0	0.1739...	-1.0	-0.601...	-1.0	0.0845...	-0.5690...	0.0444...
notfoun...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.5	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
payment...	-1.0	-1.0	-1.0	-1.0	-0.666...	-1.0	-1.0	-0.5625	-1.0	-1.0	0.5185...	-1.0	-0.633...	0.5	0.0	-1.0	-1.0	-1.0	0.5	-1.0	-1.0
payment...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.5	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
postingf...	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.670...	1.0	1.0	0.173...	1.0	0.0	1.0	0.738...	1.0	1.0	1.0	1.0	1.0	1.0
replyfor...	-1.0	-0.468...	-1.0	-1.0	-1.0	-1.0	-1.0	-0.071...	-1.0	-1.0	[illegible]	-1.0	-1.0	-1.0	-1.0	0.0	0.0679...	-1.0	[illegible]	-1.0	-1.0
replysen...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.5	0.2222...	0.0	-1.0	[illegible]	0.5	-1.0	-1.0	-1.0	-0.0679...	-0.635...	-1.0	0.5	-1.0	-1.0
resultset...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.0	-0.310...	-1.0	-1.0
resultset...	-1.0	-1.0	-1.0	-1.0	-1.0	-0.467...	-1.0	0.0775...	-1.0	0.25	-0.084...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-0.3107...	0.0	-0.4667...	-0.666...
resultset...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.2962...	-1.0	-1.0	-0.568...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-0.467...	0.0	0.0
resultset...	-1.0	-1.0	-1.0	-1.0	-1.0	0.1666...	-1.0	0.0333...	-1.0	-1.0	-0.044...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-0.467...	0.0	0.0

Figure 4. Relations between patterns

Source: Own study using ProM

This section provides only some insights into potential results that may be achieved by application of process mining techniques on website logs. These however show the following characteristics of the model:

1. typical analysis results e.g. duration, users, etc. may be delivered,
2. frequently used paths may be studied as well as patterns identified; however the focus should be on relation of these paths to paths envisioned by a website developer or enabling to monetize a user,
3. usability connected events (e.g. unresponsiveness of the elements and long requests) can be extracted – given the right granulation of steps,
4. on every step of the analysis, a detailed goal needs to be addressed (questions that should be answered need to be identified).

The above mentioned characteristics, if associated with the website logs' mining goals regarding usability, may greatly contribute to achieving goals of the analysis. Those goals can be achieved without building custom usability-related analytical systems (lowering the costs) while also providing clear conclusions from each step.

Conclusions

The model proposed in the paper provides general guidelines for monitoring the e-commerce websites' usability and presents suggestions for usability improvement that are applicable for every e-commerce website. Because of limited space, the example validation presents only a brief overlook on the possible outcomes of application of the model. Further studies are required for defining more patterns and quality results which can be extracted by process mining in comparison with other approaches.

The paper also includes an overview of the related work in the field. It describes current areas of e-commerce website analysis listed by management studies and presents possibilities of utilizing user-centered usability improvement architectures for the companies. The future work will focus on logs from multiple processes, studying users' browsing patterns and the identification of additional usability issues. Providing more user-focused results may allow for predicting browsing patterns for specific groups of users, enabling for the customization of a website on-the-fly.

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POPRAWA UŻYTECZNOŚCI STRON INTERNETOWYCH W *E-COMMERCE* POPRZEZ WYKORZYSTANIE TECHNIK EKSPLORACJI PROCESÓW

Streszczenie: Obecnie mnóstwo uwagi w obszarze *e-commerce* jest przykładane do poprawy szeroko rozumianego doświadczenia użytkownika (ang. *user experience*). Ze względu na dużą konkurencję na rynku strony internetowe o profilu *e-commerce* muszą udostępniać usługi skupione na użyteczności i jakości samej usługi. Do osiągnięcia tego celu mogą wykorzystywać analizę zachowań użytkownika, opisanych poprzez sekwencje akcji wykonywanych przez niego na portalu. Celem artykułu jest zaproponowanie podejścia dla zastosowania metod eksploracji procesów w celu analizy logów stron internetowych, aby odkryć ścieżki i wzorce zachowań użytkownika na podstawie interakcji z portalem. Odkryte w ten sposób wzorce mogą zostać użyte do analizy problemów związanych z użytecznością. Artykuł prezentuje ogólny model służący poprawie jakości serwisów internetowych typu *e-commerce*, bazując na wynikach eksploracji logów. Badania przedstawione w artykule pokazują, iż możliwa jest analiza i poprawa strony internetowej, bazując na rezultatach uzyskanych dzięki zastosowaniu metod eksploracji procesów na logach stron. Aplikacyjny charakter i użyteczność wyników są potwierdzone analizą danych pochodzących z jednego z wiodących portali *e-commerce* w Polsce.

Słowa kluczowe: eksploracja sieci, eksploracja procesów, analiza stron internetowych, użyteczność, *e-commerce*