

# A Survey of Process Mining for Customer Management <sup>†</sup>

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**Abstract:** Currently, organizations are experiencing rapid growth in the digitization of their processes, which generates a high availability of data and metadata in information systems generated by the activities of operations and support areas. This is important for business because it allows them to analyze and understand the customer journey to provide a better experience to consumers and generate value in organizations. One way to analyze the customer journey is to use process discovery to obtain an optimal process model. There are several process discovery algorithms that allow for analyzing different business process models. In this paper, we focus on the customer experience because we have found that this is a trend in business that has rarely been addressed using process discovery by means of event logs. Thus, in this study, we conduct a literature review of primary articles about the use of process discovery algorithms using event logs from information systems to provide a better understanding on this topic. As a result, we have found that Heuristic Miner, Alpha Miner, and Inductive Miner are the most used algorithms for customer process discovery. Finally, we explain our findings about process discovery in the customer experience and why this is an emerging topic.

**Keywords:** process mining; process discovery; customer journey; event log; machine learning

## 1. Introduction

Process mining is a new science that allows organizations to identify activities and resources [1]. Process mining is based on the combination of both business process modeling and machine learning [2]. There is a gap between traditional models based on process analysis and data-centric analysis techniques; process mining is responsible for closing this gap [3]. It is composed of a set of techniques that improve the performance, conformance, and quality for organizations' business processes [4,5]. Process mining uses event logs as the main input data [4–6], obtained from various information systems such as customer relationship management, enterprise resource planning, etc. [7,8]. Within an event log, each row represents an event and each column an attribute. Each event must have three essential attributes (case ID, activity label, and timestamp) [5,6]. Process mining techniques are process discovery, conformance checking, and process enhancement [6,9].

Process mining is not only applied to business processes, but also to customer journey analysis [10]. Its application in customer journey analysis shows a more comprehensive approach that allows for improving the customer experience [10,11]. The main interest in this topic is due to the constant increase in event logging, from which knowledge can be extracted and detailed process information can be provided, and there is a pressing need to optimize and support business processes in a dynamic and competitive environment [12].



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Therefore, this survey may be useful for future research on process mining in customer behavior analysis, as it gathers valuable information from previous primary work on algorithms used in discovery and/or compliance verification techniques, which was not previously found in similar studies. We have structured our survey as follows: In Section 2, we show the methodology of the literature review. In Section 3, we show the results of the literature review. Finally, in Section 4, we discuss the results, and in Section 5, we describe our conclusions.

## 2. Materials and Methods

In order to search the literature for papers that are related to the use of process mining to analyze the customer experience and customer journey, we used the following search string in the Scopus database:

TITLE-ABS-KEY ("Process Mining" AND ("Customer Journey" OR "Customer Experience") AND (survey OR review OR "Systematic Overview" OR "Systematic Literature Review")). We only found one review article among the twenty-two top IS journals; however, this study was conducted in 2016 and focuses on the evolution of an ERP in a business analysis context, also obtaining trends in the application of process mining in the customer experience [13]. We consider necessary a review of the current state of operational process management related to the customer experience. In order to carry out this study, we have posed the following research question:

RQ: What have been the improvements in the area of process mining regarding process management applied to the customer experience?

In order to solve this question, we chose the main words to be process mining, customer, customer experience, and customer journey, and searched in the Scopus database, defining the following search string: TITLE-ABS-KEY ("Process Mining" AND ("Customer Journey" OR "Customer Experience" OR "Customer\*")) AND PUBYEAR > 2018 AND PUBYEAR < 2024 AND (LIMIT-TO (SUBJAREA, "COMP")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (EXACTKEYWORD, "Process Mining")) AND (LIMIT-TO (OA, "all")).

The search resulted in 32 primary studies between 2019 and 2023, the distribution by year is shown in Figure 1; however, for the purpose of this survey, 15 were selected, taking as a reference that the study contains the terms CJM, services, sales, commerce, experience, and miner, with emphasis on the topic of process mining to analyze the customer journey and customer experience.

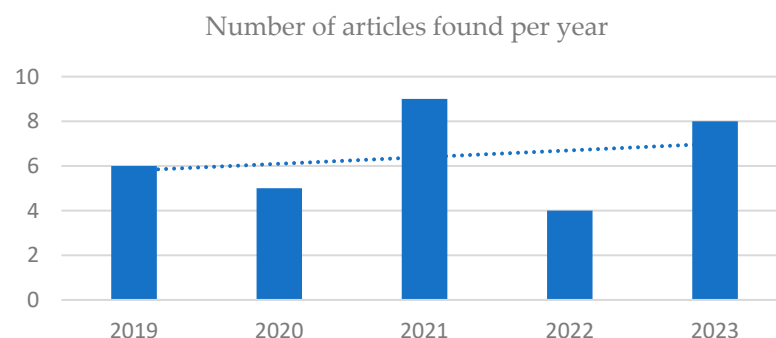


**Figure 1.** Evolution of articles studied in the present work for each year, selected in the search string.

## 3. Results

In this section, we answer the research question proposed in Section 2. We have classified the 15 papers selected according to the field of study and the process mining models that have been used, as shown in Table 1. We can see that the 15 papers were

selected having as a reference the terms CJM, services, sales, commercial, experience, and miner, with emphasis on the topics of process mining to analyze the customer journey and customer experience.

**Table 1.** Process mining applied to customer experience topic.

| Study Field                      | Process Mining Algorithms                                                | Description                                                                                                                                  | Publishing Information           |
|----------------------------------|--------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------|
| Customer Service                 | Inductive Miner                                                          | An approach that predicts the next events by leveraging business process models.                                                             | Bernard and Andritos (2019) [14] |
|                                  | ProM Framework and Petri Nets                                            | A service process value model based on Process mining techniques and domain knowledge.                                                       | Zhou et al. (2020) [12]          |
|                                  | Long Short-Term Memory (LSTM), Direct Follower Graph                     | An approach LSTM model to find probabilities for events and generated a visual decision-making process model graph.                          | Hanga et al. (2020) [6]          |
|                                  | Heuristic Miner                                                          | An online process prediction framework using features generated based on Heuristic Miner Algorithm.                                          | Tarig et al. (2021) [15]         |
|                                  | Heuristic Miner                                                          | Applying Heuristic Miner Algorithm, to discover customer behavior patterns.                                                                  | Chiang et al. (2023) [16]        |
|                                  | Inductive Miner, Heuristic Miner, $\alpha$ -Miner, Fuzzy Miner Algorithm | A sales process model to predict consumer behavior patterns based on process mining techniques.                                              | Tridalestari et al. (2023) [3]   |
| Manufacturing                    | $\alpha$ -Miner Heuristic Miner Inductive Miner Direct Follower Graph    | A method relying on categorizing the products according to how they follow the production path based on process mining methods.              | Duong et al. (2021) [17]         |
|                                  | Heuristic Miner                                                          | A model to improve flexible Heuristic Miner to build a service-oriented process value model based on a manufacturing product service system. | Zhou et al. (2021) [18]          |
|                                  | GPT-2 Direct Follower GraphLIME Model                                    | An automated process discovery framework for the manufacturing process and a process monitoring system.                                      | Moon et al. (2022) [19]          |
| Customer Relationship Management | Inductive Miner                                                          | A new approach of generating customer traces from CRMs to improve the customer experience.                                                   | Osman et al. (2019) [2]          |
|                                  | ProM Framework                                                           | A framework to mine processes from CRM data.                                                                                                 | Banziger et al. (2019) [1]       |
| Others                           | ProM Framework, DISCO tool, K-means                                      | A collaborating process mining and data mining framework for selling and shipping e-commerce C2C.                                            | Tridalestari et al. (2022) [20]  |
|                                  | Hidden Markov model, Long Short-Term Memory (LSTM)                       | A customer journey mapping (CJM) automation through model-level data fusion.                                                                 | Okazaki et al. (2022) [21]       |

Table 1. Cont.

| Study Field | Process Mining Algorithms | Description                                                                                                             | Publishing Information         |
|-------------|---------------------------|-------------------------------------------------------------------------------------------------------------------------|--------------------------------|
|             | Inductive Miner           | A method to extract associative rules based on intuitive preference settings, process mining, and correlation distance. | Bin Ahmadon et al. (2023) [22] |
|             | HIAP framework            | A framework that uses process mining techniques to analyze customer journeys.                                           | Wolters et al. (2023) [11]     |

This table summarizes our findings from the 15 papers of the research conducted on process mining models related to customer experience. Three main areas were found (customer service, manufacturing, and customer relationship management). The process mining algorithms were mapped for each paper as shown in the “Process Mining Algorithms” column, and a brief description of the paper and the frameworks it uses is shown in the “Description” column.

In Table 1, we can see that the three main fields are customer service (CS), manufacturing, and customer relationship management (CRM); other fields like selling or shipping are considered in “Others”. In Table 1, for customer service, we used a process mining algorithm for predicting events related to the business process model or the customer journey [6,14], defining a service process value model with domain knowledge [12] and predict customer behavior patterns [3,15,16]. In manufacturing, process mining algorithms are used to predict or discover the production path for products or services [17–19].

On the other hand, process mining algorithms in customer relationship management are used to generate customer trace activities, forming CRMs to improve the customer experience. Finally, in “Others”, process mining algorithms help to analyze the customer journey [11] or build frameworks for selling and shipping e-commerce [20], the automation of CJM [21], or extracting associative rules regarding intuitive preferences [22].

Eight of the fifteen articles presented in Table 2 have metrics and results; we can see metrics related to machine learning like accuracy [6,11,14,15], recall, and precision or F-measure [11,15]; causal dependency like footprint conformance [19]; and cluster distance like Davies Bouldin’s value [20] and correlation [22]. Only two papers have metrics related to process mining, fitness, and precision [2,3].

Table 2. Process mining applied to customer experience topic.

| Process Mining Model                                                     | Me1trics                        | Results | Paper                             | Process Mining Model                               | Metrics                | Results   | Paper                           |
|--------------------------------------------------------------------------|---------------------------------|---------|-----------------------------------|----------------------------------------------------|------------------------|-----------|---------------------------------|
| Inductive Miner                                                          | Accuracy                        | 0.9     | Bernard and Andritos (2019a) [14] | Heuristic Miner                                    |                        |           | Zhou et al. (2021) [18]         |
| ProM Framework and Petri Nets                                            | -                               | -       | Zhou et al. (2020) [12]           | GPT-2 Direct Follower Graph LIME Model             | Footprint Conformance  | 0.7653    | Moon et al. (2022) [19]         |
| Long Short-Term Memory (LSTM), Directly-Follow Graph                     | Accuracy                        | 0.912   | Hanga et al. (2020) [6]           | Inductive Miner                                    | Fitness, precision     | (1, 0.92) | Osman et al. (2019) [2]         |
| Heuristic Miner                                                          | Accuracy, recall, and F-measure |         | Tarig et al. (2021) [15]          | ProM Framework                                     | -                      | -         | Banziger et al. (2019) [1]      |
| Heuristic Miner                                                          | -                               | -       | Chiang et al. (2023) [16]         | ProM Framework, DISCO tool, K-means                | Davies Bouldin’s value | 0.383     | Tridalestari et al. (2022) [20] |
| Inductive Miner, Heuristic Miner, $\alpha$ -Miner, Fuzzy Miner Algorithm | Fitness and Precision           | (1, 1)  | Tridalestari et al. (2023) [3]    | Hidden Markov model, Long Short-Term Memory (LSTM) | -                      | -         | Okazaki et al. (2022) [21]      |

Table 2. Cont.

| Process Mining Model                                                           | Me1trics | Results | Paper                    | Process Mining Model | Metrics                     | Results | Paper                           |
|--------------------------------------------------------------------------------|----------|---------|--------------------------|----------------------|-----------------------------|---------|---------------------------------|
| $\alpha$ -Miner<br>Heuristic Miner<br>Inductive Miner<br>Direct Follower Graph | -        | -       | Duong et al. (2021) [17] | Inductive Miner      | Correlation                 | 0.734   | Bin Ahmaddon et al. (2022) [22] |
|                                                                                |          |         |                          | HIAP framework       | Accuracy, Precision, Recall |         | Wolters et al. (2023) [11]      |

This table summarizes the metrics and results of the 15 studies according to the model of process mining mentioned in Table 1. The results shown do not have a unit since they are represented as a percentage or a value between 0 and 1.

#### 4. Discussion

It is evident that we could use three algorithms (Heuristic Miner, Alpha Miner, and Inductive Miner) to analyze the customer journey and customer experience, which are found in almost the same papers, segmented in the areas reviewed. Also, to graph the process model, the Direct Follower Graph is used.

For the metrics of the papers summarized in the metrics and results table, two papers analyze metrics, e.g., fitness and accuracy [2,3], to contrast the resulting process model with the event logs.

#### 5. Conclusions

We conducted a literature review to study the process mining methods for the customer journey and customer experience, using Scopus as a source to collect the studied articles. With the selection criteria we defined, 15 articles from 2018 to 2023 were analyzed to answer the proposed research question. Customer service, manufacturing, and customer relationship management were found as the main topics. Heuristic Miner, Alpha Miner, and Inductive Miner were the most used process mining algorithms. Most of the reviewed articles use process mining algorithms as part of the proposed framework to obtain the business process model. A small number of articles analyze the process mining metrics to contrast the model with event logs, called conformance checking (e.g., fitness and accuracy); only 2 of the 15 articles were found to have fitness and accuracy results.

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