WHITEPAPER

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SG Analytics
Life's Possible

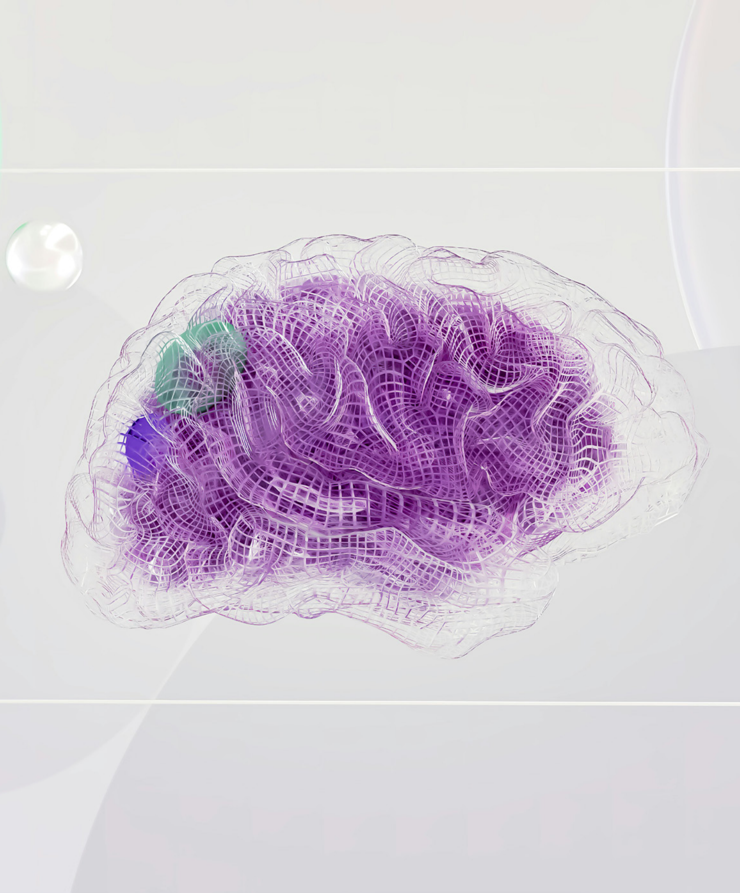
Customer Journey Analytics

IN THE AGE OF AI

EXECUTIVE SUMMARY

Enhancing Customer Journeys with AI

In today's hyper-connected digital landscape, understanding the customer journey has become a strategic imperative for businesses. The integration of artificial intelligence (AI) into customer journey analytics presents a unique opportunity to not only enhance customer experiences but also to predict and personalize interactions at scale.



Customer journey analytics enables data-backed decisions to improve customer experiences. However, with increasing digitization, the scope for customer journey analytics is expanding, along with the challenges of data integration, data quality, and real-time recommendation-led decisions.

Process mining, augmented with data, is the best approach for deriving thoughtful and meaningful insights into customer experience in this paradigm. It examines event logs in the customer journey, modeling these logs to enhance processes further for specific insights and recommendations. Meanwhile, with the current advancements in generative AI (GenAI), there is additional potential to automate, identity patterns, and personalize the customer journey. At the heart of all of this, it is important to enable data safety and quality.

This whitepaper explores the current state of customer journey analytics and the power of unlocking process mining to help companies master their customer experience outcomes in the age of AI, enabling true digital transformation and providing best-in-class value for customers.

The Interconnections between Customer Journey Map and Customer Journey Analytics

From buying a phone online to choosing a complicated software subscription, the decisions customers make today, as they choose to buy a product or a service, are far more complex than a single click of a button. Companies are increasingly relying on building visual customer journey maps to understand their buyer personas, needs, and the path customers take to address those needs. A well-crafted customer journey map can help identify key customer experiences, challenges, and pain points in simple, intuitive ways. It can also help companies make the journey from awareness to purchase much smoother for customers. But is it enough to simply visualize the journey a customer might take and brainstorm changes to improve that experience?

Embedding Customer Journey Analytics into Customer Experience Roadmaps

Customer journey analytics enables a deeper, data-driven understanding based on every interaction customers have with a business. It unlocks insights at various points in the customer journey, helping companies identify key trends and take actionable steps to enhance the customer experience. From segmenting customers to performing detailed analyses of patterns, sentiments, churn rates, buying behavior, etc., customer journey analytics is becoming increasingly sophisticated.

Companies are leveraging data more than ever to ensure greater personalization. A compelling example of this is Netflix. The streaming giant leverages AI-powered customer journey analytics to create hyper-personalized viewing experiences for its users. By analyzing vast amounts of data on individual viewing habits, content preferences, browsing behaviors, and even the time of day users watch content, Netflix dynamically tailors its recommendations in real time.

This level of personalization goes beyond merely suggesting popular shows. It includes personalized thumbnails, customized content categories, and even determining which new releases should be prominently featured on a user's home screen. By continuously analyzing every touchpoint along the customer journey – from the initial signup to ongoing interactions – Netflix ensures that users feel they are discovering content uniquely suited to their tastes. This approach not only improves user engagement and satisfaction but also reduces churn, contributing directly to revenue growth.

Now, let us explore the differences in customer journey choices from the customer's perspective. For example, Emma, a tech-savvy millennial, discovers a new productivity application (app) through Instagram advertisements, compares features on the app's website while reading user reviews, and signs up for a free trial using her Google account. Meanwhile, John, a senior executive, learns about the same app from a colleague at a conference, schedules a demo with a sales representative to understand its enterprise capabilities, and decides to purchase a company-wide license after a trial period. While both Emma and John ultimately adopt the productivity app, their journeys to reach their goal differ significantly based on their personas and preferences.

As this example illustrates, two separate personas can pursue two different journeys to achieve the same goal. For companies, adapting to these diverse journeys and personas is increasingly urgent, as customer attention span and mindshare for products is decreasing with more choices in the market. Consequently, maintaining customer loyalty has become more difficult. A strong understanding of customer needs and ability to optimize for the best experience can serve as a winning business strategy. Forrester's CX Index[1] analysis has shown that companies with higher customer experience (CX) scores are, over the long term, better positioned for growth compared to their competitors. In business terms, it translates to enhanced lifetime value of customers, with an increased probability of buying more frequently and in greater quantities from a company when their experience is delightful.

Challenges with Enabling Customer Journey Analytics

Facilitating customer journey analytics is not easy. Consider a simple digital payment transaction: while a customer is making a payment from a mobile device, multiple steps must work in tandem across various systems with real-time data flow. However, there are multiple challenges in enabling a seamless experience at scale.

First, the volume of data itself has exploded. From social media data on the interests of the customer to demographic data of customers who are buying from a company, transaction data on orders and payments, behavioral and psychographic data – these different points of information reside in various databases and in multiple structured and unstructured information formats. Overreliance on a single source of information, such as website analytics (which many journey analytics solutions tend to do), can lead to inaccurate results.

Timing is another crucial factor. Nowadays, companies cannot rely on the annual Net Promoter Score or Customer Satisfaction Survey and hope to delight customers. In the age of social media, reactions are instantaneous, and both the cost of a failure and the benefit of a delightful experience are widely publicized.

This is especially true for certain moments in the customer journey. Behavioral science highlights the 'peak-end rule[2],' which suggests that a few moments remain vividly etched in memory. For example, a checkout experience could be a peak-end moment. After conducting thorough research and deciding to buy a product, if the experience falters at this point, the customer may remember the entire journey with the memory of that one negative moment. Therefore, companies must ensure their customer experience does not fail during these peak-end moments. Additionally, it is essential to smooth out the experiences leading up to these points.

1. Forrester Customer Experience Index
2. Peak-end rule

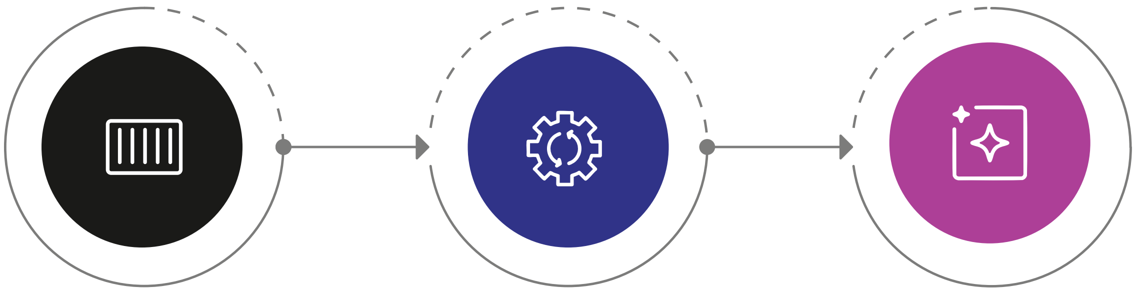
Introducing Process Mining as an Approach to Forward Looking Customer Journey Analytics

This is where the power of process mining can be integrated with the traditional methods of customer journey analytics. Simply put, process mining uses event-based data to unlock process-related information, allowing us to discover, analyze, and improve actual customer experience processes. It fills the gap between machine learning (ML), data mining, and process analytics.

Process mining is a recent addition to the field of customer journey mapping, but it has been extensively used in other disciplines, such as treatment processes and audit processes.

In fact, the most advanced applications in customer journey analytics involve combining process mining with data to enable advanced analytics.

Key Steps for Process Mining



Event Log Creation

Provide data extraction in required formats

Process Disovery and Conformance

Assess behavioral information in event logs

Balance between underfit/ overfit the event logs

Process Enhancement

Replay event log on model created, using methods like trace clustering

1.

It begins with the creation of event logs, involving data extraction in specified formats that can be retrieved later.

The event log is a crucial component of process mining for customer journey analytics . It captures the sequence of activities that occur during a customer's interaction with a company across various touchpoints. A typical event log structure[3] includes:

Case ID

This could be a customer ID or a session ID, allowing for the tracking of a single customer's entire journey across multiple interactions.

Resource, Activity, and Timestamp

This includes a combination of channels, the timing of activity, and movement between channels with timestamps. Additional attributes, such as demographic and behavioral segments, product categories, and outcomes, can also be included.

By structuring event logs in this way, companies can gain a comprehensive view of the customer journey, enabling them to identify common paths and variations, detect bottlenecks or pain points, analyze the performance of different channels or resources, segment customers based on their behavior, predict future customer actions, and optimize the journey accordingly.

To create comprehensive event logs for process mining, data must be extracted from various systems and stored in a centralized warehouse, which can then be referred to for all possible analysis. Once extracted, the data needs to be processed to ensure quality and consistency.

One must then standardize, enrich, and reduce noise within the data so that companies can create high-quality event logs, which form the foundation for effective process mining in customer journey analytics. This ensures that subsequent analysis and insights are based on accurate, consistent, and comprehensive data, leading to more reliable and actionable results for improving customer experiences.

Once the event logs are created, process discovery algorithms can build a process model to capture the behavioral information present in the log[4].

The workflow and mathematical foundations analyze the relationships between activities in the event log. It uses a set of ordering relations (e.g., direct succession, causality, parallel) to construct a process model. The algorithm creates a workflow net, a type of Petri net, that represents the process. This automated process discovery provides a solid foundation for developing process algorithms in process mining.

3. Extracting and Pre-Processing Event Logs, Dirk Fahland

4. Augusto et al., "Automated Discovery of Process Models from Event Logs: Review and Benchmark," in IEEE Transactions on Knowledge and Data Engineering, vol. 31, no. 4, pp. 686-705, 1 April 2019, doi: 10.1109/TKDE.2018.2841877.

By leveraging benchmark testing and a systematic approach, creating effective data models becomes essential for capturing the complexities of real-world processes. Key to this is the integration of task analysis and process control, which enables more accurate and adaptive process algorithms.

Additionally, the use of data mining techniques can enhance the discovery of hidden patterns within event logs, while establishing standardized benchmark frameworks ensures that new algorithms can be objectively evaluated for performance and scalability across different applications.

However, it is not without its limitations. The algorithm struggles with loops, as it has difficulty accurately representing short loops in processes. It may also fail to correctly identify all parallel activities, especially in complex processes. It assumes a complete and noise-free log, which is often not the case with real-world data.

Other alternative approaches include the following:

2. Heuristic Mining

Heuristic Mining is designed to be more robust to noise and incompleteness in event logs.

Frequency and Dependency Measures

It uses the frequency of events and sequences to determine the importance of activities and connections. Dependency measures are calculated between activities to determine their relationships.

Advantages

By considering frequency, it can distinguish between main behavior and exceptional cases. It can still produce meaningful models even with incomplete logs. The resulting models are often more understandable than those produced by the Alpha Algorithm.

3. Fuzzy Mining

Fuzzy Mining is particularly useful for simplifying complex processes and managing unstructured processes.

Approach to Simplifying Complex Processes

It leverages significance and correlation metrics to determine which elements of the process should be included in the model. Less significant activities and connections can be aggregated or removed to simplify the model.

Significance and Correlation Metrics

- Significance: Measures the importance of an activity or connection within the process.
- Correlation: Assesses how closely related two activities are in terms of their occurrence in the log.

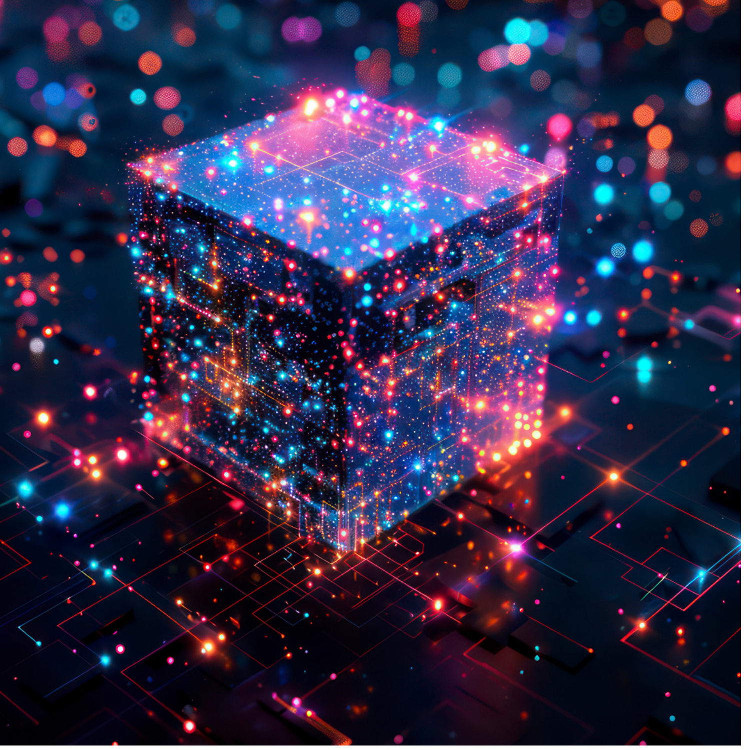
These metrics allow for dynamic simplification of the process model, enabling it to adapt to various levels of detail.

4. Inductive Mining

Inductive Mining is known for its ability to guarantee sound process models and handle infrequent behavior.

Guaranteeing Sound Process Models

It uses a divide-and-conquer approach, recursively splitting the event log to discover process fragments. The algorithm ensures that the resulting model is always sound, free from deadlocks and other anomalies.



Handling Infrequent Behavior

It can separate the main behavior from infrequent or exceptional behavior, allowing for the creation of models that capture the core process while still accounting for less common paths.

In the context of customer journey analytics, these algorithms can be applied to discover the actual paths customers take through various touchpoints. For example, the Alpha Algorithm might be used for initial exploration of straightforward customer journeys.

Heuristic Mining could be applied to analyze more complex journeys with potential noise, such as multi-channel interactions.

Fuzzy Mining might be employed to simplify and visualize complex omnichannel customer experiences.

Inductive Mining could be used to ensure that the discovered customer journey models are logically sound and capable of handling variations in customer behavior.

By leveraging these algorithms, companies can gain deeper insights into their customers' actual behaviors and experiences, enabling them to optimize and personalize the customer journey more effectively.

As a next step, conformance checking[5] compares the discovered process model with the actual event logs to identify discrepancies. This helps in understanding how well the model represents real customer journeys and where deviations occur. Conformance metrics provide quantitative measures of how well the model fits the observed behavior in the log, focusing on aspects such as fitness, precision, generalization, and simplicity.

However, all of this remains an academic exercise unless the findings are integrated back into the system. Advanced process enhancement techniques in process mining for customer journey analytics include trace clustering, variant analysis, and performance analysis.

Trace clustering groups have similar process instances to identify patterns using algorithms like K-means, hierarchical clustering.

Variant analysis identifies and compares different process variants within the customer journey.

Performance analysis calculates and analyzes key performance indicators (KPIs) to identify bottlenecks and optimize resource utilization, using methods for calculating throughput time and waiting time[6].

A strong process mining approach begins with ensuring that the right data can be unlocked from various digital and non-digital touch points. For example, data from customer relationship management (CRM) system regarding transactions. Ticketing systems offer data on customer escalations that occur when customers contact support centers or raise support tickets online. Apart from this, data from multiple application databases, such as mobile apps, is critical for understanding the customer onboarding and transaction journey. Moreover, marketing campaigns generate valuable data that helps in understanding buying behavior. Lastly, despite digitalization, there may be data lurking in various Excel sheets that need to be collated and analyzed.

From each such system, event logs can be created, and workflows can be developed to identify any breaks in the customer journey.

5. Technique for the Evaluation of Process Mining Algorithms Vahideh Naderifar, Shahnorbanun Sahran, Zarina Shukur
6. https://uu.diva-portal.org/smash/get/diva2:1900703/FULLTEXT01.pdf

How It Works in Real Applications

Let us take a practical example to visualize the key steps. Imagine a customer trying to sign up for a bank that offers multiple services, such as savings accounts, loans, and investment products. While each of these may be managed by separate departments with their own growth targets and metrics, for the customer, the bank's website, branch, or app serves as a single interface. For example, if the customer mentions that they do not wish to receive calls, any innovative marketing campaign sent to them in the future should follow this preference. Instead, the bank should provide alternate ways for the customer to interact online without receiving calls from the customer service team.

Many companies rely on web analytics tools to derive useful insights from data; however, these programs often provide an overly simplified overview of the customer journey, leading to misconceptions about user behavior on the website. For each page visited, these tools identify only the previous and subsequent pages, presenting an abstracted view of the relation between pages, exit points, and critical paths taken by customers. Today, website analytics aid companies in measuring drop-off points for different customer cohorts.

The goal of process mining with data is to expand intelligence across event logs from various sources and channels. For instance, if a customer transitions from checking out a company's ad on Google to visiting the company's landing page, then downloads the company app to sign up for the product or service, and finally calls customer service with questions about the onboarding journey in the app, an omnichannel event log would consider both the data and the journey from the customer's perspective. This approach prevents the experience from breaking due to siloed information.

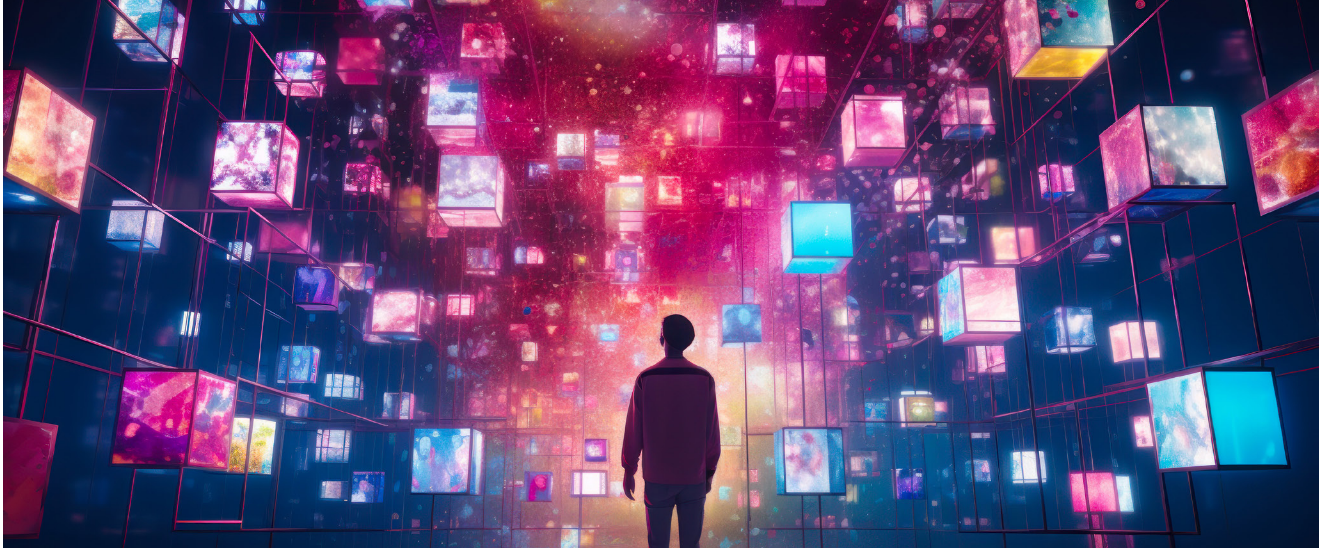
We can even predict the customer journey. Building predictive models using process data involves training on historical execution traces to forecast outcomes, numeric values, or sequences of activities for ongoing cases. For next activity prediction, deep learning approaches can be leveraged that treat event logs as sequences, like natural language processing (NLP).

The Benefits

Process mining is effective because it leverages event logs, a sequential format that is ideal for representing customer journeys. One of the primary goals of customer journey analysis is to improve it by providing personalized experiences to users while optimizing company KPIs and reducing time to action[7].

Apart from leveraging process mining to understand customer journey processes, another benefit is its ability to support customer recommendations. To generate the correct recommendation for a customer, a partial journey is compared to an event log, resulting in a recommendation that optimizes the target function based on the user's goals. This helps to personalize the customer experience. However, managing data privacy remains an important consideration throughout the journey.

7. Status and Future of Process Mining: From Process Discovery to Process Execution. In: van der Aalst, W.M.P., Carmona, J. (eds) Process Mining Handbook. Lecture Notes in Business Information Processing, vol 448. Springer, Cham. https://doi.org/10.1007/978-3-031-08848-3_13



The Road to the Future

The advent of GenAI is further enabling hyper personalization in the process mining approach to customer journey analytics.

GenAI algorithms can help identify complex patterns within event flows. With this detailed understanding, they can enhance predictive analytics by predicting future process behavior. Further, large event log datasets can be automated to identify process differences more quickly. Overall, this approach can drive more seamless digital transformation in organizations and unlock operational efficiencies at scale.

While this can be extremely beneficial for large-scale application of process mining in real-world customer journey analytics use cases, it is important to have foundational aspects in place. This begins with ensuring proper data integration across multiple sources and databases and enabling data quality to prevent hallucinations that can derail the customer journey instead of simplifying or personalizing it[8, 9].

The integration of GenAI in process mining enhances the analysis and optimization of customer journeys through advanced pattern recognition and data processing techniques. Deep learning models, such as recurrent neural networks (RNNs) and transformers, are effective at modeling sequential process data, while autoencoders can detect anomalies in process executions. Additionally, NLP techniques enable the extraction of insights from unstructured data, which can be combined with structured process data for a more comprehensive analysis and optimization of customer journeys.

8. https://www.linkedin.com/pulse/process-management-after-chatgpt-how-generative-ai-wil-van-der-aalst-lyyzc/
9. https://mindzie.com/2024/04/17/the-use-of-generative-ai-in-process-mining/

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