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ENHANCING CUSTOMER JOURNEY THROUGH PROCESS MINING: A LITERATURE REVIEW AND FUTURE RESEARCH DIRECTIONS

Igor Mandic[1] *[0009-0006-0252-1186]*

Abstract

Providing an exceptional customer experience has become a primary goal in modern business, with best-practice companies setting strategic objectives for designing and enhancing the customer journey. The customer journey approach has been applied for many years in service design to create a cohesive customer experience across all touchpoints. Advances in technology and the emergence of innovative channels have enabled companies to collect large amounts of data about customer experiences, creating an opportunity to align service design with data science to gain valuable insights. Process mining, a discipline of data science, has shown to be effective in analysing and improving business processes, with the customer journey emerging as a new area for its application. This paper aims to critically review the literature on the application of process mining to enhance the customer journey and highlight future research directions in this field. The literature search was conducted in the Scopus database using the terms "customer journey" and "process mining". Through systematic analysis, studies were selected that developed new methods for applying process mining in the customer journey and applied process mining techniques to real data sets. The research shows that, despite growing academic interest, the literature on applying process mining to the customer journey remains limited, and a unified data-driven method for analysing and mapping the customer journey is lacking. The study highlights the evident convergence between qualitative methods from service design and process mining techniques but also emphasizes the need for further research to develop an integrative approach.

Key words: *Customer Experience, Customer Journey, Service Design, Data Science, Process Mining*

[1] University of Novi Sad, Faculty of Technical Sciences, Serbia, igor.mandic@live.com

Introduction

Customer experience has become a leading business goal for most companies (Lemon and Verhoef, 2016). According to research by HBR Analytic Services, nearly three-quarters of surveyed business leaders believe that delivering relevant and reliable customer experiences is crucial to their company's overall performance, with nearly everyone considering it important in two years (HBR Analytic Services, 2017). Providing exceptional customer experiences across multiple channels and touchpoints has become critical for gaining a competitive advantage (Becker and Jaakkola, 2020; McColl-Kennedy et al., 2019). Additionally, customer experience has gained significant prominence in research across various academic disciplines, particularly in marketing, service management, and service design. The number of published academic papers on customer experience has significantly increased in recent years (Lipkin, 2016; De Keyser et al., 2020; Becker and Jaakkola, 2020; Gallardo-Garcia, 2023).

In the literature, the concept of customer experience is defined in various ways, meaning there is no single, universally accepted definition. Meyer and Schwager (2007, p. 2) describe customer experience as “the internal and subjective response customers have to any direct or indirect contact with a company”. Brakus et al. (2009, p. 53) conceptualize brand experience “as subjective, internal consumer responses (sensations, feelings, and cognitions) and behavioural responses evoked by brand-related stimuli that are part of a brand’s design and identity, packaging, communications, and environments”. Lemon and Verhoef (2016, p. 71) define customer experience as “a multidimensional construct focusing on a customer’s cognitive, emotional, behavioural, sensorial, and social responses to a firm’s offerings during the customer’s entire purchase journey.” Becker and Jaakkola (2020, p. 9) conceptualize customer experience as “nondeliberate, spontaneous responses and reactions to offering-related stimuli along the customer journey.”

Based on these definitions, we can conclude that the concept of customer experience encompasses the cognitive, affective, physical, sensory, and social reactions of customers to the offer or company, and is intrinsically linked to the concept of the customer journey. Understanding the customer journey has become a primary focus for organizations aiming to improve customer experience and enhance their business operations (Følstad and Kvale, 2018), with companies practising best-in-class approaches having clearly defined strategic goals for designing and improving the customer journey (Homburg, Jozic and Kuehnl, 2017).

The customer journey perspective has long been acknowledged as essential in the practices of leading service design agencies (Kimbell, 2011) and has also been featured in influential books in this field (Stickdorn and Schneider, 2012; Polaine et al., 2013; Stickdorn et al., 2018). According to Stickdorn et al. (2018, p. 26-27), service design is defined as “a human-centered, collaborative, interdisciplinary, iterative approach which uses research, prototyping, and a set of easily understood activities and visualization tools to create and orchestrate experiences that meet the needs of the business, the user, and other stakeholders.” Service design employs various visual and qualitative methods to explore, analyse, and design the customer journey.

The advancement of information technologies has enabled companies to collect vast amounts of data regarding customer experience through their channels, representing a significant opportunity for improving the customer journey. However, it also presents a challenge in transforming this data into actionable insights that benefit both the company and its customers. At this point, data science and service design intersect, as data science plays a crucial role in uncovering patterns within data through a quantitative approach (Kunneman, Alves da Motta-Filho, van der Waa, 2022). Various data science disciplines can be applied in service design, including process mining, which the literature recognizes as having significant potential in customer journey analysis (Aalst, W. van der, 2016; Bernard and Andritsos, 2017; Terragni and Hassani, 2018; Reinkemeyer, 2022; Halvorsrud et al., 2024). Despite the growing recognition of the importance of applying process mining to customer journey analysis, existing literature bridging these two domains remains limited.

The scientific contribution of this paper is to bridge the disciplines of process mining and service design through a critical literature review on the application of process mining methods in customer journey analysis and to identify future research directions in the application of quantitative methods in this field.

The paper is organized as follows. In the first section, we will explore the concept of the customer journey in the literature, analysing different definitions and approaches in customer journey analysis and design. In the second section, we will explore process mining methods and review existing research on the application of process mining in customer journey analysis. In the final section, we will propose future research directions that could contribute to an enhanced application of process mining in customer journey analysis.

2. Methodology

In conducting a comprehensive review of the literature on the application of process mining within customer journey analysis, we utilized the Scopus scientific database. In the database search, we used a combination of the terms “Customer Journey” AND “Process Mining” within the title, abstract, and keywords. Based on the specified criteria, 39 titles were retrieved. In the next step, a detailed analysis was conducted to select papers that focus on the application of process mining in the field of customer journey while eliminating those unrelated to this area. The papers selected for further analysis are those in which a new method for process mining in customer journey analysis was developed, or where a specific method was applied to a real dataset related to customer journeys in a particular industry. The limitation of this method lies in the possibility that there may be papers that similarly address the application of data science methods in processes related to customers. However, this research focuses on the terms “customer journey” and “process mining”, as these terms have been widely used in literature and practice for a considerable amount of time. The review of the selected papers is presented chronologically to identify the research progress in this field.

3. Customer journey

3.1 Defining the customer journey

Despite significant scientific interest in customer experience and journey, there is no universally accepted definition of the customer journey in the literature, nor is there consistent terminology. Based on their research, Zomerdijk and Voss (2010, p. 74) outline that “companies often referred to a series of touchpoints as the customer journey. The customer journey involves all activities and events related to the delivery of a service from the customer’s perspective”. Patrício et al. (2011, p. 182) describe the customer journey as "a series of touchpoints, involving all activities and events related to the delivery of the service from the customer’s perspective”. Kankainen et al. (2012, p. 221) view the customer journey as "the process of experiencing service through different touch points from the customer’s point of view." Halvorsrud, Kvale, and Følstad (2016, p. 6) define the customer journey as "a customer's interactions with one or more service providers to achieve a specific goal".

Fundamental terms related to the customer journey are touchpoint, phase, and steps. A touchpoint is the basic building block of the customer journey and is most commonly defined as the interaction between the company and the customer during the customer journey (Becker and Jaakkola, 2020; Lemon and Verhoef, 2016; Patrício et al., 2011; Halvorsrud, Kvale, and Følstad, 2016). Touchpoints can be categorized depending on who controls them - those directly influenced by the company, partner, or customer, as well as those independent (external or social) (Lemon and Verhoef, 2016). The carriers of touchpoints are the company’s channels, such as branches, contact centres, web portals, mobile apps, wearable device apps, self-service devices, social networks, instant messaging apps, SMS, and email. The customer journey unfolds through three main phases: the pre-purchase phase, the purchase phase, and the post-purchase phase (Lemon and Verhoef, 2016). Within each phase, there are specific steps that the customer goes through during the journey (e.g., online research, contacting the call centre, in-store purchase, waiting for installation, reporting an issue, contract termination).

In line with the existing literature and the purpose of this paper, the customer journey can be defined as a dynamic series of touchpoints through which the customer interacts with the offer or the company before, during, and after the purchase to achieve a specific goal.

It is important to note that the customer journey approach differs from the Blueprint method, developed by Shostack (1984) and later enhanced by Bitner, Ostrom, and Morgan (2008). This method is based on flowcharts that visually represent the steps in service delivery processes. These processes are invisible to the customer, meaning they occur without interaction between the company and the customer. We can say that the Blueprint method adopts a company perspective on service delivery, while the customer journey represents the customer's perspective.

3.2 Customer journey analysis

In customer journey analysis, companies focus on customer interactions across multiple touchpoints, encompassing all customer journey phases (Lemon and Verhoef, 2016). The concept of the customer journey is closely related to using visualization methods, specifically customer journey maps (Følstad and Kvale, 2018). Customer journey mapping is one of the fundamental practical approaches in service design and management, representing a visualization of the customer journey process over a timeline of multiple phases and steps, highlighting key events in customer interactions at touchpoints. Customer journey mapping typically includes journey phases, touchpoints, customer reactions, and key customer experience indicators. In addition to visualization, various qualitative and quantitative methods are used in customer journey analysis. Observation studies, interviews, workshops, and complex qualitative and quantitative analyses are among the most commonly employed methods, where data from various sources are integrated to create customer journey maps (Følstad and Kvale, 2018). Customer journey analysis can be applied to improve existing services as well as in the development of new services.

Customer journey mapping has been practically applied in service design for nearly two decades, and the application of this method was explored by Kimbell (2011) in three leading service design agencies. In addition to practical applications, the customer journey mapping method has found its place in leading books on service design (Stickdorn and Schneider, 2012; Polaine et al., 2013; Stickdorn et al., 2018). Stickdorn et al. (2018) emphasize that the role of customer journey maps is not just to visualize the customer experience over a certain period but also to identify problems in the customer experience and find solutions to them. Maps allow the intangible nature of service and experience to be made visible and help the service design team gain a shared understanding of the customer experience. Journey mapping is always done from the customer's perspective and follows a specific representative of a customer group (main actor). The maps have both horizontal and vertical dimensions. The horizontal dimension shows the main journey phases and steps, while the vertical dimension visualizes the customer experience for each step (storyboards), customer satisfaction levels (emotional journeys), customer engagement levels (dramatic arc), the channel with which there is interaction, stakeholders, connections to backend processes, and potential issues in each step. Both qualitative methods, such as user statements, observations, and visual content that illustrates the experience, as well as quantitative methods, like satisfaction surveys, can be used in mapping.

The literature in this field does not provide a standardized methodological approach to customer journey analysis. Halvorsrud, Kvale, and Følstad (2016) were the first to initiate the creation of a standardized approach for customer journey analysis. In this regard, they proposed an integrated customer journey model that views service delivery from the customer's perspective. In their model, they established precise terminology, conceptualized the distinction between planned and actual journeys, objective and subjective factors, and adopted foundational elements for journey visualization. Customer journey analysis based on this model relies on a comparative analysis of the service delivery process as a) a planned process, which involves how the company designed the service delivery process, and b) the actual process, representing the real customer experience during service delivery.

The customer journey analysis identifies deviations, i.e., unplanned or unnecessary touchpoints in the actual process compared to the planned process. Customer journey analysis is conducted through five phases: defining the scope of the analysis, identifying the planned journey, selecting users and collecting data, analysing the actual journey, and reporting. To achieve a comprehensive analysis of the actual journey, they used both quantitative and qualitative methods. Quantitative methods were used to collect data on the flow and duration of the process from the company's information systems. Qualitative methods included interviews and the diary method, where users recorded the service delivery process.

They applied this model to analyse the customer journeys of mobile broadband customers at Telenor, a telecommunications company. The analysis was conducted on 23 customer journeys, which encompassed 9 to 19 touchpoints each. The results showed that none of the analysed journeys aligned with the planned journey, indicating that the process contained many deviations and unnecessary touchpoints compared to how the company had planned the journey. Their analysis revealed that the customer journey does not correspond to how service providers plan it and that more detailed planning and analysis of the customer journey is necessary.

3.3 Customer journey analysis in omnichannel environment

The modern omnichannel environment presents a significant challenge for companies, as they must create a cohesive customer journey across all touchpoints. Due to technological advancements, companies have developed various channels to interact with customers, while customers have simultaneously gained the freedom to choose the channels that best meet their needs and preferences (e.g., they can explore offers online but make a purchase at a retail store, or vice versa). The consequence of numerous channels and touchpoints is the potential for a wide variety of customer journeys, which may deviate from the customer journey planned by the company. Further, advancements in technology and channels have resulted in an unprecedented surge in the volume of data that companies collect regarding customer behaviour and their experiences throughout the entire customer journey. Consequently, there is a strong need for applying quantitative methods in the analysis of customer journeys, as these methods can help generate valuable insights from the vast amounts of data collected during the customer journey.

Kunneman, Alves da Motta-Filho, and van der Waa (2022) explored how quantitative data science methods can contribute to service design projects. They conducted research in the existing literature and, through an iterative process, analysed with service designers which data science disciplines could be applied in their practice. Based on their research, they identified several data science disciplines applicable to service design, including opinion mining, physiological condition mining, process mining, insight mining, generative models, and clustering. The following section will focus on process mining, which represents "an important bridge between data mining and business process modelling and analysis" (Process Mining Manifesto, 2012, p. 172).

4. Applying process mining to customer journey analysis

4.1 Process Mining

The primary role of process mining is to discover, monitor, and improve business processes by generating insights from event logs available in information systems. This discipline's increasing significance has been influenced by the tremendous growth in the volume of event data across various information systems and the significant need for companies to enhance their business processes (Aalst, W. van der, 2016, 2012).

The starting point of process mining is the event log. Each event log refers to a specific activity that occurred at a particular moment and can be assigned to a unique case. An event log consists of a case ID as a numeric identifier, the activity that occurred, and a timestamp with the precise time of each activity. Additional attributes can be added to these minimal elements of the event log to provide further information about specific activities. In a corporate information environment, event logs are digital traces stored for any business activity in the databases of various information systems (Reinkemeyer, 2022).

There are three primary types of process mining. The first is process discovery, which creates a process model based on event logs without using any prior information. The second type is conformance, in which the process model is compared with event logs from the actual process. Conformance checking can be used to verify whether the actual process matches the model and vice versa. The third type is process enhancement, where the main goal is to expand or improve the existing process model using information about the actual process based on event logs. While conformance checking measures the alignment between the process model and the actual process, this third type aims to improve the process model (Process Mining Manifesto, 2012).

Numerous process mining applications have been developed that enable the application of this technique across various industries. Most of these applications support the visualization of business processes and a specific type of conformance checking with the process model. More advanced solutions provide automated connections with information systems (SAP, Salesforce, Oracle, ServiceNow, Workday), enabling continuous data collection (van der Aalst & Carmona, 2022). There are over 40 companies in the market that have developed process mining applications, and according to the Gartner report, the leaders in this field are Celonis, UiPath, Software AG, SAP Signavio, Microsoft, Apromore, Appian, ABBYY, Mehrwerk (Magic Quadrant for Process Mining Platforms, 2024). According to research conducted by Deloitte, the majority of surveyed companies (63%) have already implemented some form of process mining solutions (Global Process Mining Survey, 2021).

4.2 Literature review on the application of process mining to customer journey analysis

Bernard and Andritsos (2017) were the first authors to investigate the application of process mining in mapping customer journeys (CJM). They highlighted the significant potential of applying this method in customer journeys. Their work demonstrated an excellent correspondence between XES format components and CJM. The XES format (eXtensible Event Stream), developed by the IEEE Task Force, is the most accepted in process mining for importing event logs into process mining applications. The proposed CJM model is based on a hierarchical XML structure and includes the following CJM components: journey, customer, touchpoint, experience, channel, stage, and lens. They mapped the developed CJM model to the XES format, which allows further analysis in process mining applications. Then, they imported the synthesized CJM model into the Disco process mining application. Their basic model consists of a “de jure” model, which is normative and aims to manage or control the actual state of the process, and a “de facto” model, which aims to represent the actual state. In other words, the first model is the planned customer journey, and the second is what happens in customer journeys. Bernard and Andritsos, through this work, successfully bridged customer journey mapping and process mining, opening up opportunities for further research in diverse customer journey scenarios across various industries.

In their later work, Bernard and Andritsos (2018) focused on further integrating process mining and CJM, particularly in discovering CJM process models. The basic idea in discovering process models is to create a process model based on event logs in an information system. They proposed a new model called CJM-ab (CJM abstractor), which allows process mining algorithms to discover processes to abstract the CJM process model. The CJM-ab model uses four steps to represent CJM at different levels of abstraction in order to abstract the process model. In the first step, the goal is to create a process tree based on event logs. They consider the process tree method the most suitable for discovering customer journey process models. In the second step, CJM must be created based on the same event logs. They applied Bayesian Information Criterion (BIC), Calinski-Harabasz index, Markov model, and manual data processing methods in this step. In the third step, the process tree created in the first step needs to be parsed, for which they developed a script in JavaScript. In the fourth step, they transformed the CJM at different levels of abstraction of the process model.

They applied the CJM-ab model to a dataset obtained from a scientific conference where the conference organizer, in the context of the customer journey, was the service provider, and the scientists who submitted their papers to the conference were the customers. The customer journey encompassed the entire path from the call for papers through review management to the final acceptance or rejection of the paper. The dataset included 10,000 customer journeys and 236,360 activities.

Terragni and Hassani (2018) explored the application of process mining in the web environment to investigate customer journeys, predict user activities, and recommend actions to maximise specific key performance indicators (KPIs). They believe the web is ideal for analysing customer journeys as every user activity is recorded in an event. They also think that applying process mining in this area can overcome the limitations of Web Analytics tools. In their work, they created a model for analysing web customer journeys using a real dataset obtained from an internet portal selling various types of products. The dataset contained clickstream data for one month, with 10 million events and 2 million users.

Their model's core elements are data preprocessing, web log data filtering, process discovery, behaviour clustering, making recommendations, and procedure evaluation. 1) In data preprocessing, it was necessary to create a mapping function $f(u_i) = a_j$ that maps each url (u_i) to specific actions (a_j) from the set of activities $A = (a_1, a_2, .., a_m)$. They used a procedure adopted from Poggi et al. (2013), hand-written rules, and unsupervised clustering. 2) Since such a dataset of event logs contains unnecessary data that can mislead the analysis, they filtered the data and halved the total number of events. 3) For process discovery, they used the Disco application, which employs the Fuzzy Miner algorithm. 4) As customer journeys in the web environment are highly flexible, users can have very different activity flows representing deviations from the planned customer journey. Therefore, the resulting process model is unstructured, requiring manual filtering or unsupervised clustering. 5) The goal of their model is to find ways to optimise KPIs through the analysis of customer journeys. The primary KPI in their work is increasing the number of visits to product pages that match individual users rather than the page with the most popular products, which is the same for everyone. To this end, they applied a recommendation system based on collaborative filtering techniques, replacing recommended product pages based on product similarity with a more advanced technique – a collaborative filtering algorithm adopted by Hu et al. (2008). Since they did not have data on users' favourite products, they used data on time spent on a product page, frequency of visits, and similar data from customer journeys to create appropriate user recommendations. 6) They evaluated the model using the ACU (Area Under the Curve) statistical model. The results showed that their collaborative filtering algorithm had a significantly higher ACU than a simple recommendation for the most popular product page and a slightly higher ACU when considering page visits.

Arias et al. (2020) focused their research on applying process mining in mapping customer journeys in healthcare. Their study demonstrated significant possibilities for applying process mining in discovering different pathways patients might go through and analysing touchpoints through which patients pass. They conducted their case study using data from the information systems of a hospital and its associated emergency services. They applied their research to two diagnosis groups – pneumonia and acute myocardial infarction. The dataset included 6,715 cases with 523,521 events. For creating customer journey maps, they adopted the components defined by Bernard and Andritsos (2018) but adapted their meanings to the healthcare context (e.g., customer-patient). In the first step of the process mining analysis, they exported data from information systems in CSV format. Then, they split the data into two groups (cases event log and activities event log). Both datasets were uploaded to a data pool, and a new data model was created. For process analysis, they used the Celonis application. They investigated which customer journey models existed and through which touchpoints patients passed based on data from two diagnosis groups. They also examined the impact of gender and age on the path a patient took during the healthcare procedure and the impact of gender and age on the length of hospital stay.

Hassani and Habets (2021) explored the application of process mining in predicting the next touchpoint in a customer journey. The ability for a company to know the next step of the customer can allow for proactive action and timely customer support. They applied the developed model in one of the leading telecommunications operators in the Netherlands. The business goal of this operator was to eliminate all unnecessary touchpoints that repeat in customer journeys and resolve all customer requests at the first touchpoint. To achieve this, it was necessary to know which touchpoint would be next for the customer and, if possible, the type of request the customer would make (which could be just a clarification or a service cancellation).

For this research, they used two eight-week datasets, including over a million data rows and nearly half a million customer journeys. Initially, they defined touchpoints, categorised them, and analysed their frequency. They then analysed customer journeys in the first dataset using the heuristic miner algorithm to determine which touchpoint is typically next. Some sequences are typical, such as a call (conversation with an operator) followed by an order, service ticket, or logistical activity. In the second dataset, they analysed the distribution of customer journeys by the number of touchpoints (one touchpoint had 39% of journeys, two 40%, and three 14%). In addition to this data, they included data on the reasons for calls, which employees enter descriptively or select from options. This type of data is beneficial for prediction but, due to free-text entry, must be cleaned and reduced to useful information. In the model, they used logistic regression, random forest, boosted trees, and LSTM neural network. In evaluating the performance of this model, they found that predictions for some touchpoints were very weak (chat and branch), while others were very good (service technician dispatching to resolve a standard problem). They attributed the weaker results for some touchpoints to their nature, as these touchpoints can sometimes be unpredictable in user behaviour.

4.3 Research findings

Although process mining is a relatively new discipline, it has found an excellent application in analysing and improving business processes across various industries, and one of the new fields where it can find successful application is customer journey analysis. The synergy between process mining and customer journey analysis offers significant opportunities for better understanding and enhancing customer experience (Halvorsrud et al., 2024).

Even though the number of studies in this field is still limited, existing research has made significant progress in connecting these two approaches. Bernard and Andritsos (2017, 2018) were the first to develop a methodological framework for applying process mining in analysing and planning customer journeys, laying the groundwork for further research in this area. Terragni and Hassani (2018) demonstrated the importance of applying this method in the web environment, which is somewhat more suitable for implementation, and showed the value of process mining in creating data-driven recommendations based on customer journey data. Arias et al. (2020) illustrated how applying process mining to customer journeys in the healthcare industry can provide crucial information necessary for enhancing patient experience and how patient data (e.g., gender, age) can be used in process mining analysis to obtain valuable insights. Hassani and Habets (2021) showed how process mining can contribute to predicting subsequent touchpoints in the customer journey, thus improving the customer experience, and highlighted the correlation between specific touchpoint characteristics and prediction capabilities.

Based on the review of existing literature, it is evident that despite the significant contributions of current research, there is a lack of a unified process mining method for analysing and mapping customer journeys, and further research in this area is needed to establish a standardized approach.

5. Future research direction and discussion

The application of process mining in customer journey analysis can significantly contribute to uncovering valuable insights that cannot be obtained through the analysis of a limited scope of customer journeys. Qualitative methods, applied to a narrower sample of customer journeys, are essential for deeper analysis and understanding of the entire journey, including all touchpoints and the overall customer experience. On the other hand, the value of applying process mining in this area lies in its ability to cover a broader range of customer journeys and additional customer data, which can contribute to a better understanding of the complete customer journey.

Despite the great potential for applying process mining in the analysis and design of customer journeys, there are certain challenges in applying process mining in this area. Halvorsrud et al. (2024) highlight several challenges in the joint application of process mining and customer journey analysis: 1) Capturing the end-to-end journey: the success of process mining application depends on its ability to cover all touchpoints and events in the customer journey, and not just limit itself to the analysis of internal processes; 2) Organizational borders in the service delivery network: the customer journey spans different organizational units and often different organizations, which poses a challenge for process mining to cover all data from different organizations; 3) Non-detectable touchpoints: Process mining relies on IT system records, but touchpoints like direct in-person conversations with customers often go unrecorded in these systems and thus remain invisible in process mining analysis; 4) Capturing the customer experience: customer experience is a multidimensional concept that accumulates throughout the entire journey, requiring deeper qualitative analysis that cannot be quantified in a way that can be analysed through process mining.

To further enhance the application of process mining in customer journey analysis and design, future research should prioritize the following areas:

- Standardization of process mining models to enable more consistent analysis and mapping of customer journeys
- Creation of an integrated framework that combines qualitative methods with process mining techniques to encompass all touchpoints and the entire customer journey
- Development of a model that merges process mining with quantitative customer experience metrics, offering a more comprehensive understanding of customer experience
- Expansion of process mining methodologies to incorporate additional customer data, yielding deeper insights into the customer journey.

6. Conclusion

Providing exceptional customer experience through multiple channels and touchpoints has become crucial for gaining a competitive advantage in modern business. To ensure an outstanding customer experience, companies must set strategic goals in customer journey design. The numerous channels through which companies interact with customers and the large number of touchpoints significantly increase the number of different customer journeys, which may differ from those planned by the company. The complex service environment with multiple channels presents a significant challenge for companies, as it requires creating a cohesive customer journey across all touchpoints. At the same time, companies collect vast amounts of data on customer behaviour and experiences throughout the customer journey. Therefore, in addition to existing qualitative methods, it is essential to incorporate quantitative methods into customer journey analysis to generate new insights from the large amount of available data. Process mining in customer journey analysis can significantly contribute to uncovering essential insights that are not attainable by analysing a limited number of customer journeys. The advantage of process mining lies in its ability to encompass a large volume of customer journeys and additional customer data, allowing for a more comprehensive understanding of the entire journey. Although existing research in this field highlights the promising potential of process mining, it remains relatively unexplored and offers significant opportunities for further research and development. The convergence between qualitative methods from service design and process mining methods is evident, and future research and practice should foster the development of an integrated approach to customer journey design that addresses the challenges and limitations of existing methods.

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