

Connecting the Digital Dots - Can Customer Journeys be Analyzed Purely from Event Logs?

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Abstract. Customer journeys increasingly unfold through digital channels. This offers new opportunities for service providers to extract insights from customers’ digital traces. However, as customers move across organizational boundaries and modes of interaction, it is difficult to capture the complete end-to-end journey with process mining or similar methods. This experience report investigates how accurately service providers can reconstruct actual customer journeys using only internal system data. We apply a dual-perspective approach that combines an empirical investigation involving customers with a reconstruction of the same journeys based on digital traces from internal service systems. Our findings highlighted key challenges in reconstructing customer journeys. While planned or expected touchpoints were well covered (89% in our case), ad-hoc or deviating touchpoints proved more challenging to capture (33%). Crucially, quality issues tended to arise not within an organization, but in the transitions between them—precisely where visibility is most needed. Effective reconstruction of customer journeys requires a systematic approach to bridge silos and enable a unified view, especially when service delivery is partly outsourced.

Keywords: Customer Journey · Process Mining · Empirical Study · Coverage

1 Introduction

The recent wave of digital transformation has led to customers leaving behind more digital traces than ever before in the information systems of service providers. Every digital interaction generates system-level data, creating new possibilities for analyzing service use and user behavior. Service ecosystems typically involve a main provider and multiple supply-chain partners, each operating their own IT infrastructure. Together, these actors form a Service Delivery Network (SDN) [11]. This fragmentation of the service system complicates coordination and may result in poor customer experience. Although SDNs, in principle, may leverage digital traces to improve cross-organizational insight, doing

so requires substantial coordination and resources. As a result, few attempts are made to track user experiences over time. This lack of holistic, time-aware analysis creates a digital blind spot in understanding how services are encountered by end users. The concept of *customer journeys* is central to this effort, offering an outside-in view of service delivery from the end user’s perspective [16]. A customer journey consists of a series of touchpoints—moments when users interact with the SDN, either digitally or physically. While many of these touchpoints leave digital traces, others do not: they may be unlogged, occur offline, or involve actors outside the formal SDN. As a result, significant parts of the journey may remain invisible to the service provider.

In this study, we investigate to what extent service providers can reconstruct actual end-to-end customer journeys based solely on internal system data. We combine two complementary perspectives: an empirical investigation involving real customers, and a retrospective reconstruction of the same journeys based on the digital footprints they leave within the SDN. This dual-perspective design allows us to evaluate how accurately the reconstructed journeys reflect the actual sequence of events experienced by customers. It also provides a basis for identifying potential gaps, overlaps, and blind spots, and contributes to advancing the knowledge needed to automate the discovery and analysis of real-world customer journeys based solely on system-level data. In summary, this paper makes two contributions. First, using a *case study of an online bookstore*, it examines how organizations can structure their systems to enable automated reconstruction of customer journeys from backend data. Second, it presents *empirical findings* on the extent to which such journeys can be extracted from real-world system logs.

2 Background

Customer journey methodology offers a range of approaches to investigate end users’ encounters with service offerings. Despite the growth of the field, it remains fragmented and lacks standardized methods and established standards [6,16,7]. Nevertheless, a central feature is the visual representation of journeys as customer journey *maps*—mostly portraying customer touchpoints chronologically along a time axis. The second dimension varies widely and may include elements such as emotions, communication channels, or user strategies. A particular language that emerged is the Customer Journey Modeling Language (CJML), which we adopt in this paper for the empirical investigation. CJML is a domain-specific modeling language developed to represent service processes from the perspective of the end-user⁵. Customer Journey Analysis (CJA) employs CJML as its modeling language to empirically investigate individual service experiences over time and across multiple channels [7]. The process begins with an analysis of the SDN to establish the planned journey(s), typically through methods such as process mapping, mystery shopping, and service walk-throughs. Customers are then recruited early in their journeys and participate in an initial interview to capture motivations and expectations. They are instructed to keep a *structured*

⁵ <https://www.cjml.no/>

diary, documenting all encounters with the service system. Once the journey is completed, a *follow-up interview* is conducted to review the diary entries and reflect on the actual experience. Touchpoints are chronologically ordered and annotated with relevant attributes, such as instrumental properties and customer feedback. Deviations from the planned journey are categorized as ad hoc touchpoints (unexpected additions), irregularities in sequence or timing, failing touchpoints (unwanted outcomes), and missing touchpoints.

In contrast to CJA, process mining reverse engineers the as-is process behavior from events sourced from information systems [1]. Initially, it was targeted to business processes of an organization, but process mining has seen widespread adoption among many domains including the analysis of customer journeys [2,8,9,12,13]. Journeys have been analyzed, e.g., through web log analysis [12] and also information such as customer emotions or their characteristics have been subject to analysis with process mining methods [3,4]. Zilker et al. [17] noted that customer-centered analysis is still challenging in the case of end-to-end journeys spanning several systems and when including user experience. Case studies on customer journey analysis have been previously published [8,9]. In fact, our previous work [9], reported on an analysis of event data from the same case provider; however, the empirical evaluation involving the actual customers, as done in this paper, is lacking.

There is also empirical work in the field of process mining that investigates the organizational use of process mining [10,14]. Major research directions are the impact of process mining and its use by analysts [10]. Many case studies, also in the domain of customer service, have been reported [5]. Our case study focuses on the data collection phase, which was reported to have a low level of thoroughness in related works [5]. Through the dual-perspective design, we aim to shed light on data accessibility in the customer journey domain. Data availability has previously been identified as a challenge [18]. However, we are not aware of existing work that investigates this in the domain of customer journeys in a real case and combines process mining and CJA methodology.

3 Case

Bookis⁶ is a Norwegian consumer-to-consumer (C2C) marketplace for buying and selling used books via web and mobile platforms. The service integrates payments and logistics, aiming to make literature more accessible while promoting reuse. Given its platform model, Bookis has a strong focus on customer experience and is actively working to improve visibility across partner systems. This study was conducted as part of the Smart Journey Mining research project, in which Bookis participated as an industry partner. As part of the collaboration, Bookis provided customer journey data and supported the mapping of planned touchpoints. Further details about the platform’s business model and functionality are available in previous work [9].

⁶ <https://bookis.com/>

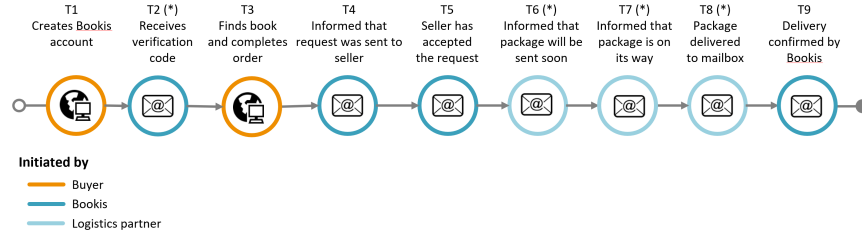


Fig. 1: Planned customer journey for a buyer. Touchpoints are color-coded according to the actor initiating the communication. An asterisk indicates touchpoints where variations occur.

This paper focuses on the buyer’s customer journey, that is, the journey of a customer purchasing a book on the Bookis platform. Fig. 1 illustrates the planned journey, i.e., the expected sequence of touchpoints, beginning with T1, where the buyer creates an account on the Bookis website. At touchpoint T2, the buyer receives an email containing a verification code to complete the account creation process. Once the account has been created, the buyer can proceed to order a book. At T3, the buyer locates the book, selects the desired version and seller, and completes the payment. The next touchpoint, T4, is an email from Bookis to the buyer confirming that the request to purchase the book has been sent to the seller. T5 is another email from Bookis informing the buyer that the seller has accepted the request. This email also includes information about when the package will be shipped, an option to track the package, and an option to chat with the seller. At touchpoint T6, the logistics partner sends an email to the buyer notifying them that a package will be sent soon. T7 is a subsequent email from the logistics partner indicating that the package is on its way. T8 is an email from the logistics partner confirming that the package has been delivered to the mailbox. Finally, T9 is an email from Bookis confirming delivery.

As indicated in Fig. 1, touchpoints T2 and T6–T8 represent points of variation in the planned journey. T2 will only occur for customers who wish to create an account using their email address; for those who log in with Google, it does not occur. Touchpoints T6–T8 vary in how the logistics partner communicates with the buyer about the package. In some cases, the partner may use one or more channels, such as email, push notifications via the logistics app, or SMS. Regardless of the channels used, the information conveyed and the sequence of T6–T8 remain consistent. Due to these variations, the planned customer journey will contain a different number of touchpoints for different buyers.

4 Method

This study investigates the reconstruction of actual customer journeys based solely on internal data from a SDN. To this end, we adopted a multi-method approach supporting a *dual-perspective* investigation. First, we applied the CJA

method [7] to gather detailed, empirical accounts of real customer journeys. This *outside-in perspective* served as the ground truth for the customer journeys. In parallel, we collected all available digital traces related to the same customers from the back-end systems of the SDN. This enabled an independent *inside-out reconstruction* of the journeys, based exclusively on logs, events, and interactions recorded across the infrastructure of the SDN. Ethical approval was granted by SIKT - Norwegian Agency for Shared Services in Education and Research (reference No. 794702).

Empirical investigation with customer journey analysis We applied CJA as described in Sect. 2 to the buying journey of Bookis, with us acting as the seller of the books to create a controlled environment. We employed a convenience sampling strategy, recruiting students both for practical reasons and because they represent a key target group for Bookis. Recruitment and data collection took place from December 2024 to March 2025. Participants were recruited via posters on the University of Oslo campus. Written informed consent was obtained from all participants prior to data collection. To be eligible for inclusion, participants had to be currently enrolled students at the University of Oslo, have experience with digital services and online shopping, and not have an existing user profile on Bookis.no, allowing account creation to be included as part of the journey.

A total of 39 individuals signed up during the recruitment period. Of these, one person declined participation due to the study’s scope, and twelve were unresponsive to e-mails regarding consent and scheduling. From the initial 39 responses, 21 participants were selected to take part in the study with 20 of them successfully completing. Participants were between 22 and 31 years old ($M = 25.0$, $SD = 2.7$). The gender distribution was slightly skewed, with 11 men and 9 women. The participants’ fields of study ranged from humanities and social sciences to health sciences and technical disciplines. Most of them were in their fourth or fifth year of study.

Data-based reconstruction with process mining The reconstruction process started with understanding Bookis’ objectives, the information they were logging and how these data sources could be accessed. Next, Bookis provided example data and demonstrated the structure of their dataset. After several iterations, we identified the essential data that needed to be logged and suggested modifications to achieve this. Once the changes were implemented, we began our study asking the participants to buy used books from us. After the study, Bookis provided the participants’ journey logs and obtained shipment logs from the logistics partner for parcel tracking.

Bookis provided data in two distinct files: the shipment logs in JSON format and their own logs in CSV format. To ensure privacy, Bookis removed information such as geolocation, IP addresses, and e-mail addresses. The data was then cleaned to remove irrelevant data and records outside of the observation period. This resulted in the final data structure: userID (assigned participant

ID), event (touchpoint), subject/description (touchpoint description), channel, sender, timestamp, and URL. To properly link the shipment data, we extracted the attributes event, description, sender, and timestamp from the transportation events associated with the parcel. Once both data structures were aligned, differences in timestamp formats remained across the datasets. These were standardized using Power Query to ensure consistency. Finally, events were renamed for consistency with the main event log yielding a unified dataset ready for analysis.

To analyze the data, we used the process mapping functionality of the academic version of Apromore⁷. Apromore takes the event log and provides a visual process map indicating the flow of the events. These maps allowed us to visualize the SDN. Furthermore, with the participants' diaries, we were able to compare participant-reported events and system logs.

5 Results

The reconstructed customer journeys revealed a mix of planned and ad-hoc interactions across varying durations and levels of complexity. Participants encountered an average of 9.9 planned touchpoints and 2.7 ad-hoc touchpoints. In total, the number of touchpoints per journey ranged from 9 to 28. The journey spanned an average of 7.8 days per participant, with individual durations ranging from 4 to 22 days. Table 1 provides the detailed breakdown per participant, including the number of planned and ad-hoc touchpoints, total number of touchpoints, and the duration of the journey.

The combination of diary data and follow-up interviews provided detailed accounts of participants' actual journeys and corresponding experiences. Although this paper focuses on the objective touchpoint data rather than the participants' subjective experiences, the rich qualitative input revealed several variations from the planned journey described in Sect. 3. Participants also reported several ad-hoc touchpoints that were not captured in the event logs. Most of the issues reported by the participants were related to T3 (find book and complete order), with one user reporting that the site crashed when trying to complete an order. In addition, touchpoints involving communication with the seller and customer service, as well as package tracking, were frequently mentioned but not consistently captured by the event logs.

The event log consisted of 886 events captured over a three-month period, distributed across 20 distinct cases (each corresponding to a study participant). Each case followed a unique sequence of events, resulting in 20 trace variants. This is likely due to differences in user navigation and variations related to touchpoints T5-T8. In all cases, a total of 47 unique event types were recorded. Overall, user navigation accounted for 44%, internal logs for 35% and communication with the customer for 21% of the events. The average case duration was 9.5 days, ranging from 4 to 29 days. A substantial portion of the events were related

⁷ <https://apromore.com/academic-alliance>

Table 1: Overview of planned, ad-hoc, and total touchpoints per participant, and journey duration (days).

Participant	Planned	Ad-hoc	Total	Duration
ID1	8	4	12	7
ID2	11	0	11	6
ID3	10	1	11	5
ID4	10	0	10	5
ID5	11	0	11	11
ID6	11	2	13	4
ID7	9	7	16	5
ID8	10	2	12	6
ID9	9	0	9	9
ID10	11	17	28	22
ID11	10	2	12	7
ID12	11	3	14	7
ID13	10	2	12	7
ID14	10	1	11	9
ID15	8	2	10	6
ID16	10	5	15	6
ID17	9	1	10	11
ID18	9	1	10	6
ID19	10	3	13	6
ID20	10	1	11	10
Sum	197	54	251	
Average	9.9	2.7	12.6	7.8

to touchpoints T1 and T3. Customer communication represented the smallest share of recorded events; however, this category also demonstrated weaknesses in the logging process, particularly when customer interactions occurred outside of the planned journey.

Fig. 2 shows the overall process map generated from the event log. Because of its size and complexity, we highlight two zoomed-in segments in Fig. 2b and Fig. 2c. Fig. 2b shows Bookis’ internal system logs related to order completion, along with a customer notification event. These events correspond to touchpoints T3 and T4 in the planned journey. The first event in this segment also reveals an application error captured by Bookis. Fig. 2c depicts events from the logistics partner, corresponding to touchpoint T6 and the progression toward touchpoint T7. The sequence begins with an internal event from the logistics partner, followed by two customer notifications, and continues with events that document the advancement of the delivery process.

Turning from the sequence of events to their classification, Table 2 presents different categories of event types in the event log along with illustrative examples. From 47 unique events, user navigation (C1) amounts to 15 distinct event types. These events are primarily associated with touchpoint T3 and provide insights into how the buyer navigates the platform to achieve their goal. The next category (C2), comprises Bookis’ internal logs, which include twelve different event types. Although these events are not directly related to customer interactions, they are crucial for managing internal processes and coordination with logistic partners. In category C3 there are events related to Bookis’ communication with the customer, which are very relevant for analyzing the customer

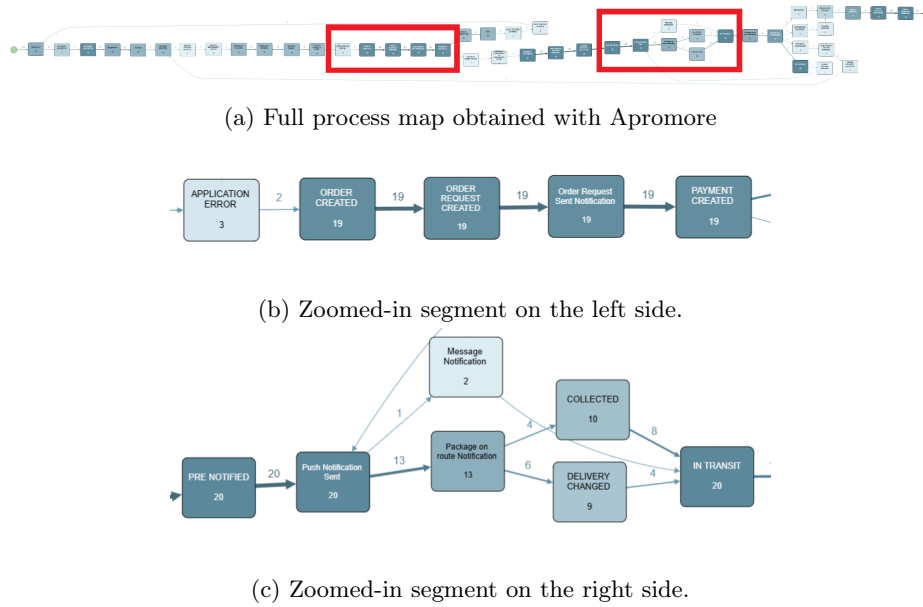


Fig. 2: Composite figure showing the full process map (a) and two zoomed-in segments (b) and (c), corresponding to the areas marked.

journey. These represent interactions in which information is communicated to the customer via email related to touchpoints T2, T4, T5, and T9 from the planned journey and encompass four distinct event types. The internal events from the logistics partner log (C4) capture nine event types related to the delivery handling process. These events range from the receipt of the package from the seller to its final delivery. They primarily serve internal tracking and operational control purposes within the logistics provider. Finally, C5 focuses on customer-facing notifications throughout the delivery process. There are seven event types on activities that ensure that customers receive timely and relevant information about their deliveries.

Comparing the recordings and the empirical study, Table 3 shows the extent to which the planned and ad hoc touchpoints documented by participants in their diaries were also captured in the event data. In total, 197 planned and 54 ad-hoc touchpoints were documented. The number of planned touchpoints ranged from 8 to 11 with an average of 9.9 across participants. Each participant encountered all planned touchpoints and no participant reported fewer touchpoints than those in the planned journey. The coverage of planned touchpoints in the event logs was high on average (89%). This number could have been closer to full coverage if not for challenges in consistently logging touchpoint T1 and the absence of touchpoint T2 from the logging. In contrast, greater variation was observed in the ad-hoc touchpoints, which ranged from 0 to 17 touchpoints with an aver-

Table 2: Number of event types of different categories present in the event log.

Category	Example Events	#Types
User Navigation Events (C1)	- Search started - Product clicked - Product added to cart	15
Bookis Internal System Logs (C2)	- Payment captured - Order request accepted - Order submitted	12
Bookis Customer Notification (C3)	- Delivery registered notification - Order request approved notification	4
Logistics Partner Internal Logs (C4)	- Collected - Deviation - In transit - Ready for pickup	9
Logistics Partner Customer Notification (C5)	- Package on route notification - Delivery notification	7

age of 2,7 across participants. The average coverage for ad-hoc touchpoints was substantially lower (33%). For participants who reported ad-hoc touchpoints, the event logs frequently failed to capture these interactions. The ad-hoc touchpoints not captured in the event logs primarily involved communications with customer service and the seller as well as issues related to tracking. For example, Participant 1 contacted customer service to address issues during the order process, while Participant 10 engaged in repeated communication with the seller through Bookis’ chat service to resolve a refund request. Several buyers reported difficulties tracking their packages through the Bookis website.

In conclusion, the company’s event log data did not fully capture the breadth of user interactions specifically when it comes to ad hoc interactions.

6 Discussion

Previous research has shown that service providers often have only partial insight into the customer journeys they are responsible for—sometimes lacking awareness of the sequence of touchpoints or even of their existence [7]. In this case, the main service provider had good control over the planned journey, but we identified variations in touchpoints managed by the logistics partner. These variations were revealed both through the mystery shopping assessment and the empirical study. For instance, the dispatch of notifications depended on whether the customer had installed the logistics partner’s mobile app—an external detail that is difficult for the main provider to anticipate or control.

In the case of Bookis and many other new businesses that utilize a C2C-model, ensuring a positive user experience for both sides of the platform is essential. This focus on user experience is crucial for attracting and retaining users, particularly due to the network effects at play. Network effects refer to the phenomenon in which each new user added to the platform increases its value for all existing users [15]. For Bookis, the more users they can attract and retain, the easier it becomes for users to buy and sell books. For Bookis,

Table 3: Coverage (%) showing the fraction of planned and ad-hoc touchpoints captured in the event log.

Participant	Count		Coverage (%)	
	Planned	Ad-hoc	Planned	Ad-hoc
ID1	8	4	87	50
ID2	11	0	81	-
ID3	10	1	90	0
ID4	10	0	90	-
ID5	11	0	90	-
ID6	11	2	90	100
ID7	9	7	89	28
ID8	10	2	90	50
ID9	9	0	89	-
ID10	11	17	91	18
ID11	10	2	90	0
ID12	11	3	91	33
ID13	10	2	100	50
ID14	10	1	90	100
ID15	8	2	87	50
ID16	10	5	90	20
ID17	9	1	78	0
ID18	9	1	89	0
ID19	10	3	90	33
ID20	10	1	90	0
Average	9.9	2.7	89	33

this gap has direct implications. Our analysis shows that while digital traces of planned touchpoints are largely captured (coverage 89%), deviations remain significantly under-logged (coverage 33%). Insights from the study are already informing improvements in system design and partner coordination, which will better support both buyer and seller experiences on the platform.

To improve coverage, Bookis will (1) implement structured logging for customer service interactions (chat and email), (2) negotiate standardized event formats with logistics partners to ensure visibility into key delivery steps and failures. Already Bookis have (3) implemented customer feedback loops (in-app prompts post-delivery) to validate and enrich journey data. Failures in visibility, especially in transitions between platform and logistics partners, can impact user satisfaction, support load, and ultimately user retention on the platform. From a *managerial perspective*, two main insights emerge: **(1)** Journey continuity depends on partner integration: Capturing full customer journeys requires structured data-sharing and aligned logging standards across the SDN. **(2)** Ad-hoc events need more attention: Internal logging systems must evolve to include non-linear, customer-initiated actions such as support chat and reordering attempts, critical for understanding user frustration. Finally, as an orthogonal but very important concern, responsible data use is key: As journey mining capabilities scale, transparency and alignment with GDPR principles, e.g., through privacy-preserving process mining techniques, are essential for maintaining user trust and ensuring ethical data practices.

Limitations. This study has several limitations. It focuses on a specific C2C marketplace which may differ from other, similar platforms. The buying journey examined is simplified, excluding scenarios such as purchasing multiple books or

buying from different sellers. To reduce uncertainty, we deliberately controlled the seller’s role and avoided complications such as unaccepted orders or failed deliveries. This enabled comparison against a common, planned journey with minimal variation but reduces the generalizability of the findings. Furthermore, there are multiple ways to delineate steps in a customer journey. For example touchpoint T3 “Finds book and completes order” could reasonably be decomposed in several sub-activities. This simplification is an inherent challenge in modeling and we acknowledge that it can influence the reported coverage. Finally, the data were gathered from a convenience sample of 20 students without existing Bookis accounts. This recruitment strategy further narrows the applicability of our findings to broader user groups or other platforms.

7 Conclusion

This experience report contributes a dual perspective case study on a customer journey in a C2C marketplace for buying and selling used books. Our findings indicate that organizing customer data in terms of individual journeys—by leveraging their continuous digital footprint—can offer service providers valuable insights into customer behavior and reveal opportunities for service improvement. The dual perspective showed to be important in revealing that many ad-hoc interactions are not captured and, consequently, several interesting deviations would not have been possible to analyze with process mining methods alone.

In future work, our aim is to further refine and generalize the applied dual-perspective method beyond this single case study and provide recommendations for a successful integration of both perspectives. Another promising direction for future work lies in investigating whether customer experience itself, and not just a proxy for it in terms of deviating touchpoints, can be inferred from these digital traces. This would open the door to more personalized and responsive service innovation based on process mining methods.

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