

Exploring Automated Customer Journey Analysis with User Journey Games

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Abstract. The growing digital footprint of service consumption offers new opportunities for analyzing interactions between service providers and customers at scale. Customer Journey Analysis (CJA) is an effective approach for capturing and visualizing customers' detailed interactions and experiences with a service provider, using the Customer Journey Modeling Language (CJML) as its modeling language. However, the qualitative nature of CJA makes the approach resource-intensive. In this paper, we investigate a weighted game approach to customer journeys, described through CJML, which enables analysis beyond the event logs of a single system and allows for the capture of journeys extending outside the traditional data space. The game approach generates graphs with weighted edges calculated using a gas function, a metric that quantifies the "patience" drained from the customer throughout their journey. The objective is to assess the two analysis approaches, explore how they could be integrated, and investigate whether gas can reflect customer experience. The results show that, although the weighted game approach initially seems to offer useful insights into customer experience, there are significant discrepancies in the lowest-scoring experiences. This indicates that further research is needed to draw firm conclusions about the correlations. However, the method used for comparison can serve as a basis for future studies. Moreover, combining the qualitative depth of CJA with the scalable analytics of user journey games offers the potential for insights at both individual and aggregated journey levels and can, in the future, help advance the development of automating the journey analysis process across the entire customer journey.

Keywords: Customer journey · User journey games · Customer experience · Automated journey analysis.

1 Introduction

Human experience is a complex and multifaceted phenomenon encompassing cognitive, emotional, and behavioral responses. This complexity is acknowl-

edged in both service research [15] and the human-computer interaction community [10]. User- or customer experience (CX) is inherently subjective, being shaped by the situational context and the customer’s internal state, which may shift over time [14]. The digital footprint generated through customers’ service consumption represents a valuable resource for customer-oriented service providers. While these data traces can provide valuable insights into how individual customers interact with their services and products, they offer only a partial view of the customer experiences. Many service providers also struggle to transform the fragmented data into coherent traces that reflect individual users’ repeated interactions over time - especially when the evidence spans both digital and non-digital touchpoints and crosses multiple systems [9]. Hence, there is a growing need for effective tools and methods to analyze interactions between customers and service providers.

The concept of the customer journey refers to the complete sequence of interactions as experienced and perceived by the customer (or any type of end user) when engaging with a service system to achieve a specific goal [17]. It is a fundamentally customer-centered concept, emphasizing how the service is experienced from the customer’s point of view—over time, across channels, and involving multiple service providers. To support this perspective, the Customer Journey Modeling Language (CJML) [8] has been developed as a formal language for precisely describing customer journeys. Customer Journey Analysis (CJA) [6] leverages CJML to empirically investigate individual, actual journeys. It relies on customer involvement and rich qualitative data, which makes the analysis both labor-intensive and time-consuming.

Process mining, on the other hand, is an automated, data-driven approach that reconstructs processes based on event logs extracted from information systems [1]. Originating from a business-centric perspective, process mining has in recent years been applied to customer-facing processes in an effort to automatically map customer journeys [3]. However, several challenges remain: most customer journeys span multiple systems, some touchpoints leave no detectable traces, and automated measures of CX have significant limitations [9].

In this paper, we introduce the user journey game approach to CJML-modeled journeys obtained through CJA, as a means of analyzing customer journeys and investigate the potential synergies of combining CJA and the game approach. Both approaches have strengths and weaknesses, which will be explored in this paper. For instance, where process mining focuses primarily on the sequence of events, the games approach also considers the agents performing these actions. The user journey games— a weighted game approach, has shown promising ability to capture certain events happening in a company [13]. Hence, games can seem to infer organizational events out of data. Furthermore, the game approach generates graphs with weighted edges that are calculated using a gas function, a metric that quantifies the energy or “patience” drained from the customer throughout their journey. However, it is not known whether there can be a correlation between the gas function and the customers’ experiences. The paper explores whether the gas function can indicate the customer experience

(CX) of a touchpoint or of a customer journey. This is investigated using existing journey data from a previous case study investigated with CJA. These analyses are compared with the user journey game approach both qualitatively, on the insights they provide, and quantitatively, highlighting touchpoints and journeys scoring below 4 or 5 on the CX 5-point scale, as these are the most commonly selected ratings [16]. In this way, we connect service research with game-theoretic analysis, providing a foundation for further studies of automated, end-to-end customer journey analysis.

2 Background

To support the description and comparison of CJML and the game approach, we present an illustrative fictional case with a corresponding dataset simulating five customer journeys in an online shopping scenario. These journeys are modeled using CJML and then translated into a user journey game graph to explain and compare these two approaches.

2.1 CJML and Customer Journey Analysis (CJA)

CJML is a formalized approach to customer journeys, including terminology and visual notations. The language takes the perspective of the end user, whether a customer, patient, or any other human role. A customer journey is defined as a sequence or constellation of touchpoints involved for a customer to achieve a specific goal or a desired outcome [8]. CJML distinguishes between hypothetical (planned) journeys and real (actual) journeys. It also clearly separates observable, objective attributes—such as the choice of communication channel—from the subjective customer experience. The visual notation used in CJML consists of two types of specialized process diagrams that highlight the actors involved in the journey and the chronological sequence of steps—referred to as touchpoints. In this paper, we focus on the standard customer journey diagram, where each touchpoint is illustrated as a circle with a channel icon at its center and a border indicating the initiating actor.

The fictional journey involves coordinated interactions between three actors: the customer, the online bookstore, and the logistics partner, progressing through digital channels and ending in physical delivery. Figures 1 and 2 represent, respectively, the two service process states in CJML: (1) The hypothetical state - planned journey, (2) the real state, with an individual user - actual journey. The planned journey reflects how the service process is implemented by the service provider(s). While service providers should strive for actual journeys to comply with the planned journey, deviations often occur—resulting in ad-hoc touchpoints, as illustrated below the dashed line in Figure 2.

The five fictional customers follow different journey paths: the first three experience no deviations from the planned journey, apart from minor variations in touchpoint timing. Customer 4 encounters a long waiting period and contacts customer support to inquire about the delivery. The fifth customer has a

similar experience but receives a follow-up call from the customer support (as shown in Figure 2). The fifth customer has a similar experience but triggers two deviations—first by contacting support, and then by receiving a follow-up call initiated by the provider.

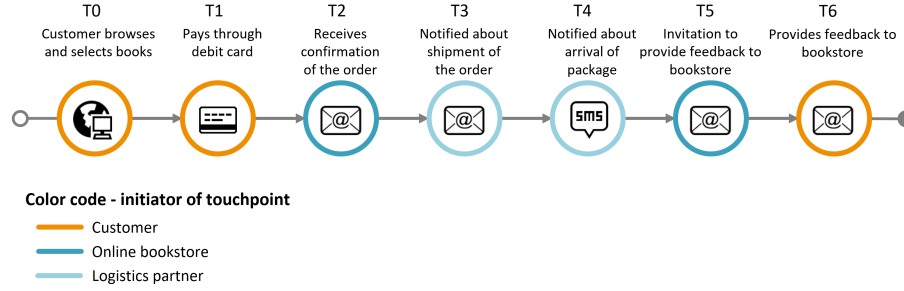


Fig. 1. The planned journey as intended by the bookstore.

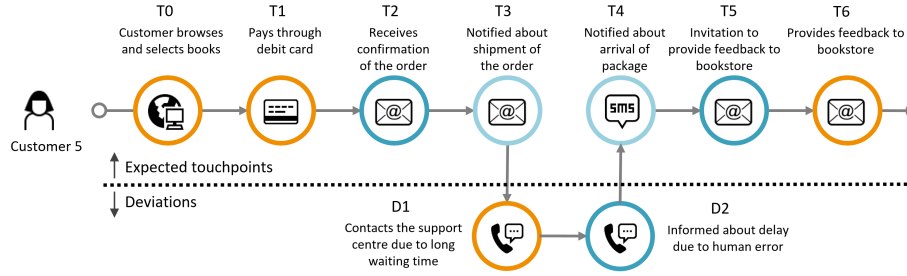


Fig. 2. The actual journey of Customer 4, including a deviation illustrated below the dashed line.

The CJA method is used to investigate and evaluate both planned and actual customer journeys. It consists of five phases: the first two focus on mapping the planned journey using traditional methods like process mapping and mystery shopping. The remaining three phases involve the empirical investigation of actual journeys. Participants are recruited early in their engagement with the service and take part in an initial interview to capture expectations and context. Throughout the journey, they document their experiences using a structured diary. For each touchpoint, participants are asked to report their experience (CX), both by providing free-text feedback and by rating the touchpoint using a Likert scale. Once the journey is complete, a follow-up interview is conducted. This debriefing session includes a systematic review of the touchpoints in chronological order, particularly because the diary may occasionally be incomplete or contain

gaps. The resulting data are modeled as annotated CJML diagrams, capturing touchpoints, user feedback, and deviations from the planned journey.

2.2 Games

Games naturally model the interaction between multiple self-interested actors [5]. We consider two-player games where one player is controllable, which in Figure 3 is the online bookstore, and the other player, is uncontrollable, here, the customer buying a book. The game starts in an initial state where either the service provider or the customer might take an action. In each turn of the game, players with available actions in that state can try to take one of the available actions or decide not to. In case both players decide for an action, the uncontrollable player, the customer, receives priority. However, if only one player has available actions, that player must decide for one of the available actions. The next state of the game is determined by the current state of the game and the chosen action.

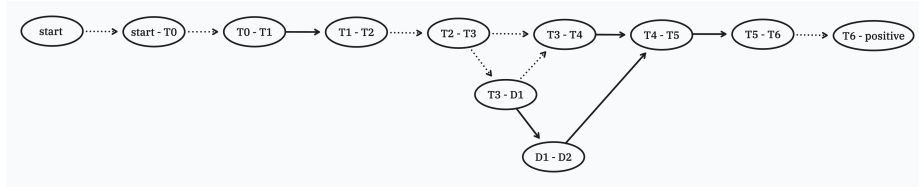


Fig. 3. User journey game for exemplary data.

When analyzing games from the customers’ perspective, one is interested in strategies for the controllable player – the service provider. Thereby, the users’ independence is preserved as their actions are not restrained and the service provider is responsible to guide the user through the journey. A strategy assigns an action to each state of the game [5]. To analyze weighted games, we use a formal method called *model checking* [2]. In this method, a target or successful state is defined. In the illustrative dataset, this state corresponds to the customer providing feedback to the bookstore—an outcome achieved in all observed journeys. Using the model checker, it is possible to synthesize a shorter strategy, meaning the customer can reach the successful outcome with a reduced number of steps. Compared to CJML, games use an inverted terminology. While circles in CJML denote an activity, edges (illustrated as arrows) in games denote the available actions. Controllable actions are depicted as solid lines and uncontrollable actions with dashed lines. States in games are expressed as circles containing the name of the state. The state can either be that it reached a certain state or it can include a sequence history. In our example we have included a sequence history of 1, meaning that the state (T0-T1), represents that both T0 and T1 is completed. The initial state in Figure 3 is called “start”. It provides one uncontrollable action to select a book, which in the following state, both are completed. Note how the state “T2-T3” provides two actions, one to call the service provider, where one action leads to a deviation from the planned journey.

User journey games [13], model the interaction between service provider and users as weighted two-player games [4]. The user’s ability to progress through the service is modeled by *gas*, defined as the aggregated sum of weights accumulated throughout the journey. Gas is a data-driven metric derived from the dataset using entropy and majority voting. Specifically, if most of the journeys passing through a given edge are associated with successful outcomes, the corresponding constant in the weighting formula will be positive; conversely, if most outcomes are negative, the constant will be negative.

Each interaction can either increase or decrease gas, depending on its influence on the final outcome. For example, waiting in line for customer support can be draining and reduce gas, while an effective sales pitch may increase it. If an interaction strongly contributes to a successful outcome, it receives a maximum gas values, while those leading users to abandon the journey receive minimum gas.

The weight of an edge is computed using the following formula:

$$w(e) = ((1 - H(e, L)) \cdot \text{majority}(e, L) - C) \cdot M \quad (1)$$

Here, $H(e, L)$ is the entropy of edge e with respect to user journey outcomes in dataset L , while M and C are constants controlling the scaling and aversion threshold, respectively. Further details on gas and games for user journeys are given in [13].

The exemplary dataset illustrates a fundamental difference between the visual notation of CJML and games. The game approach combines multiple actual journeys into a single aggregated representation. This allows for an comprehensive overview of possible paths and strategic choices, emphasizing the variability among the customers. In contrast, CJML is rooted in each unique journey instance, being unable to aggregate several individual journeys into one model. Instead, CJML focuses on faithfully representing the sequence of touchpoints experienced by a specific user.

2.3 Case Background

We draw on a dataset from an earlier case study [7] conducted with a telecom company, focusing on the onboarding of new mobile broadband (MBB) customers. The MBB journey was known to be complex for customers, involving both analog and digital communication channels, and extending over several days. The data was collected from $n=23$ actual journeys as part of an assessment of service quality. The planned journey, as shown in Figure 4, consists of 9 touchpoints taking customers through confirmations, dispatch of material, and the final installation of the mobile internet line.

CJA Insights Notably, the analysis revealed that none of the journeys were compliant with the planned journey; all actual journeys contained deviations. The number of touchpoints ranged from 9-19, with an average of 12. Importantly,

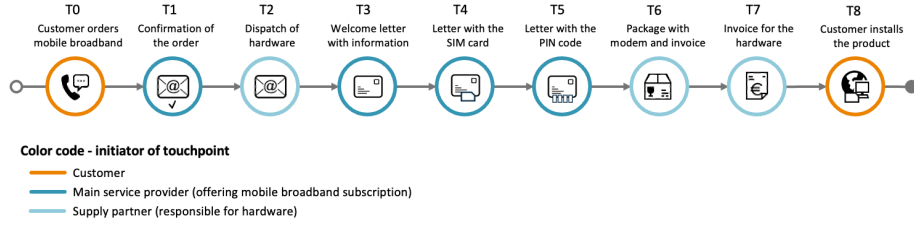


Fig. 4. The planned journey as intended by the MBB service provider.

most of the journeys were hampered by timing errors, where company-controlled touchpoints occurred in the wrong sequence—leading to customer frustration and inquiries to customer service. Finally, CJA also provided temporal insights, showing that journey durations ranged from 1 to 30 days, with an average of approximately 11 days.

CJA further revealed that for task T8 to be successfully completed, T4, T5, and T6 must all be completed, although the order in which they occur is flexible. T5, which involves obtaining a PIN typically sent by letter, may alternatively be acquired by contacting customer service. While T1 is not strictly required, customers strongly expect a confirmation after placing an order. In contrast, T2 and T7 are not necessary and tend to be counterproductive. T3 is also not deemed essential but performing it prior to delivering hardware may help reduce customer confusion.

3 Methodology

In this paper we formalize the customer journeys described with CJML as weighted games between customer and the service provider as described in [13], using the model checker UPPAAL STRATEGO [11] to compute winning strategies on these games. Lastly, we compare the two methods—CJA and the game approach—both qualitatively and quantitatively.

The objective is to assess the analytical capabilities of each approach and investigate whether gas can serve as an indicator for customer experience (CX). The method involves defining comparison criteria, collecting the relevant data, and analyzing both the similarities and the differences. The comparison focuses on the following criteria: 1) How well the insights from each approach align and where they diverge, 2) The extent to which gas reflects CX at the individual touchpoints level, both for individual customers and on average, 3) How accurately the total gas of a journey reflects the average CX score.

In the original case study [7], a three-point Likert scale was used for CX. For this analysis, the scale was expanded to five points to better capture variation when a customer rated the same touchpoint differently in the diary (immediate experience) and the debriefing interview (retrospective experience). The original endpoints (1 and 3) were transformed to 1 and 5 on the new scale, while

intermediate scores (2 and 4) were used to reflect average values when diary and interview ratings differed.

To enable meaningful comparison between gas and CX, the gas values—which originally ranged from -24.2 to 15.8—were linearly rescaled to the same 1-5 scale used for CX, where 1 indicates a poor experience and 5 a good one. Since gas can be interpreted as accumulated feedback (with positive values indicating favorable conditions and negative values indicating friction), a linear transformation was chosen to align the extremes, the lowest gas value mapping to 1 (lowest CX), the highest gas value to 5 (highest CX), and values around zero mapping to an average score. The following min-max normalization function was used to rescale gas to match the CX scale:

$$\text{gas}_{\text{rescaled}} = \left(\frac{\text{gas}_{\text{original}} - \text{gas}_{\text{min}}}{\text{gas}_{\text{max}} - \text{gas}_{\text{min}}} \right) \cdot (\text{CX}_{\text{max}} - \text{CX}_{\text{min}}) + \text{CX}_{\text{min}} \quad (2)$$

with $\text{gas}_{\text{original}}$ being the value that we want to rescale, and the static values being $\text{gas}_{\text{min}} = -24.2$, $\text{gas}_{\text{max}} = 15.8$, $\text{CX}_{\text{min}} = 1$, and $\text{CX}_{\text{max}} = 5$. The resulting averages were rounded to the nearest tenth and scores on the individual touchpoints to the nearest whole number. A difference of less than 1 point is considered acceptable, as the scale advances in whole-number increments, so such a difference can be seen as remaining on the same rating level.

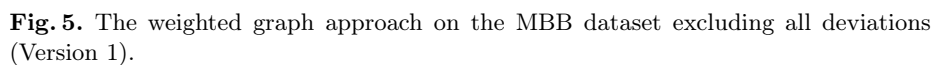
4 Results

4.1 From CJML Journeys to Games

The CJML journeys were described as a dataset in Excel, where each row represents a single touchpoint. To convert these into a user journey game, the dataset was first transformed into traces—i.e., individual customer journeys represented as linear paths of touchpoints. From these paths, a transition system was constructed. A sequence history of 1 was selected to prevent infinite loops while still aggregating journeys, avoiding an overly fragmented, tree-like structure with excessive branching. This transition system was then transformed into a game representation.

The resulting game was analyzed using UPPAAL. We synthesized a baseline strategy that ensures the user reaches a successful outcome (broadband installation completed with a positive result) and evaluated its performance in terms of steps taken and gas. An optimized strategy was then generated to minimize the number of steps while achieving the same goal, allowing us to investigate whether a shorter path to success exists. Both strategies were evaluated through simulation, analyzing metrics such as maximum number of steps, minimum and final gas values, and overall stability (e.g., ensuring gas remained above a defined threshold).

The output of this process is a user journey game graph: a state-transition model with weighted edges that represent the impact—positive or negative—on the user’s progress through the journey, as modeled by gas.



In this section, we describe and illustrate the results of applying the user game approach on the MBB dataset. Figure 5 shows the first attempt, version 1 (V1), ignoring all the deviations and incorporating solely the touchpoints that were described in the planned journey as seen in Figure 4. In the second version (V2), shown in Figure 6, we incorporated one deviation (D1), “failed to install MBB product”. This deviation was repeated in several of the journeys and directly

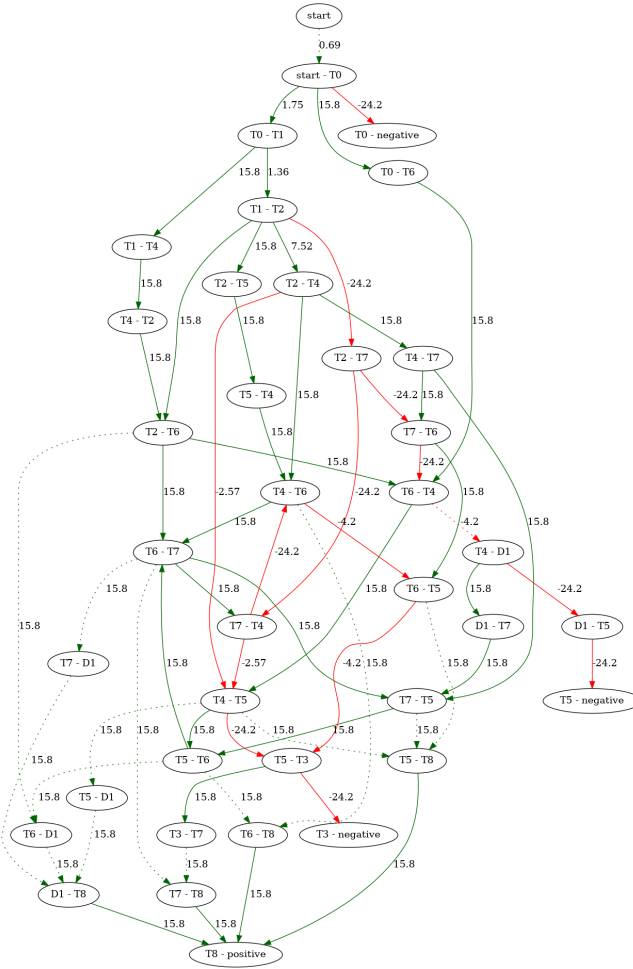


Fig. 6. The weighted graph approach on the MBB dataset including a deviation (D1) (Version 2).

affected the successful state of installing the product. All the journeys can be depicted in the graphs. A history of one is included in each state which means that it is described along with the state it came from (e.g., T1 – T2). The number on the edges represent the gas of that interaction – touchpoint, where positive interactions are marked green, and negative interaction, draining the “patience” of the customer, are marked in red. The dashed lines represent the uncontrollable actions that are triggered by the customer and the solid ones the service provider actions.

The game analysis, through the model checker, revealed that there is a shorter strategy to reach the successful state of installing the MBB product. This strat-

egy is T0 – T6 – T4 – T5 – T3 – T7 – T8. When favoring short journeys, the company is supposed to omit all “not necessary” communication, in this case T1 and T2.

4.3 Comparing Insights

Both CJA and the game approach provide insights on which touchpoints are considered necessary. This is represented in Table 1, which discloses the insights from the games, and recapitulate the insights described in Section 2.3. While both analysis methods agree that T1 is not necessary, CJA highlights that it is strongly expected by the customers, as it provides an overview of the intended process. CJA also indicated that T2 and T7 not only lack necessity but may negatively impact the experience. The user journey games comply with CJA on T2 but does not classify T7 in the same way.

Table 1. Overview of the touchpoint deemed necessary by both approaches.

Label	Description	CJA	User Game
T0	Telephone call for ordering	Necessary	Necessary
T1	E-mail confirming the purchase	Not necessary	Not necessary
T2	E-mail confirming shipped hardware	Not necessary	Not necessary
T3	Letter describing the process ahead	Not necessary	Necessary
T4	Letter containing the SIM card	Necessary	Necessary
T5	Letter containing the PIN code	Necessary	Necessary
T6	Package containing modem	Necessary	Necessary
T7	Invoice for the hardware and freight	Not necessary	Necessary
T8	Installation of the product	Necessary	Necessary

Other insights from the user journey games include that users usually had more steps after installing the system (T8) and that it demonstrates a high number of variations – insights correlating with the insights from the CJA. The graphs reveal further insights by showcasing the most negative interactions and the strategies that can lead to negative outcomes. From the graphs we can deduct information on an aggregated journey level with a historical aspect, such as depicting that the customers proceeding straight from T2 to T7 are drained of energy and can from there only choose actions that will drain them even more, either going to T6 or T4. Going to T4 and then to T6 is the only way of ending up in a successful state – which is that the customer receives the package containing the modem and installation guide. We see that the uncontrollable edges are the ones going to the installation of the MBB product or to the failing of installing (D1) in V2, meaning that the customer often must initiate this interaction.

Moreover, as mentioned in the previous section, the analysis of the game (V1) revealed a shorter strategy, which depicts that the customer could jump straight to T6 – getting the installation guide and modem, and still end up successfully

installing the MBB product, if getting the PIN-code (T3) and SIM-card (T4) straight after the guide.

4.4 Comparing Gas and Experience

As mentioned in Section 3, to compare the gas value and customer experience, we firstly investigate the touchpoints by comparing the customer experience (CX) score for one touchpoint with the gas for that same touchpoint, and secondly, investigate the score and the gas of the full journey. We investigate both on the individual and on the average level.

Investigating Touchpoints To investigate whether gas can give an indication on the users' experience of a touch point, we first investigate the accuracy of single touchpoints, then the average score of each touchpoint (from T0 to T8), and finally the touchpoints that got a score lower than 4 in the CJA.

Investigating single touchpoints. The results of investigating the single touchpoints are shown in Figure 7. The left-hand side shows the CX scores, while the right-hand side presents the rescaled gas values from Version 1 (V1) of the user journey game. A gradient color scale is used to distinguish the scores, ranging from red (score 1) to green (score 5). In V1, the numbers where the gas accurately matches the CX score are 60 out of 126 (47.6%), while including the ones that were one score away are 100 out of 126 (79.4%). When replicating the same procedure for V2, only two values changed, Customer 7 on T4 changed to 3 and Customer 10 on T4 changed to 5. However, the difference remains 1, and did not affect the result.

Comparing the average customer experience and average gas per touchpoint. The average customer experience and average gas per touchpoint are shown in Table 2. The average gas per touchpoint mapped into 5-point scale is similar in both V1 and V2. We first compared with the values including all available data, meaning no customer experience score or gas was excluded. However, since the CX data is incomplete due to some customers leaving scores blank, and because the journey concludes upon reaching T8 in the games, we also tested excluding entries that did not contain both CX and gas values. The average gas value became significantly more relatable to the average CX score from the CJA when filtering the values. From the rescaled gas values in the table, we observe that T4, T5, T6 and T7 are nearly identical to the CX scores, followed closely by T0. T2, T3 and T8 show a difference of more than 0.5 points, and T1 has the largest discrepancy of 0.8 points.

Another observation is that D1 could be seen as the opposite of T8, meaning that in the eyes of the customer the customer experience score of failing to install the MBB product (D1) could impact the CX score of T8, but not affecting the gas of T8. Including the average of D1 to T8 reduces it to 4.6 with only a 0.2 difference. However, this result cannot be filtered due to the setup.

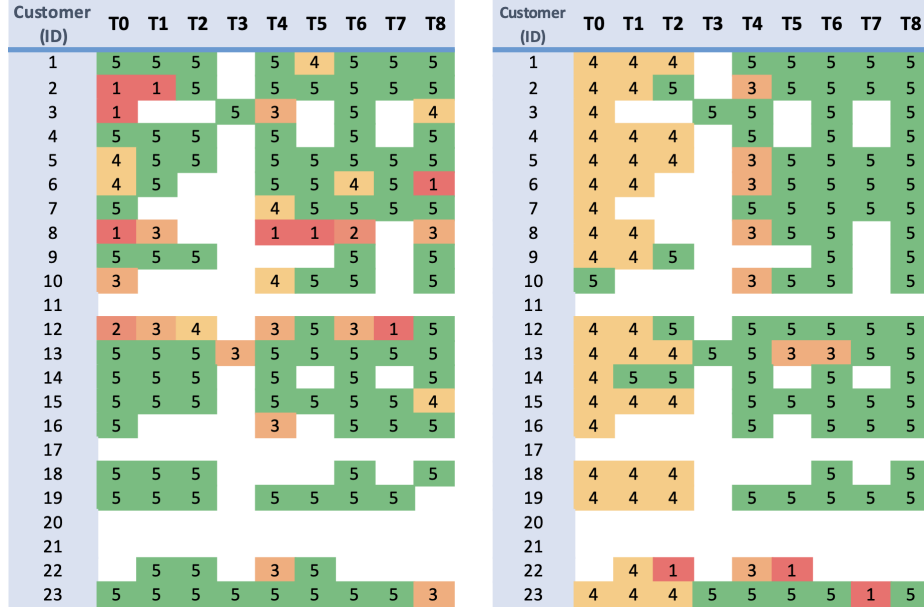


Fig. 7. Investigating the accuracy of single touchpoints. Left-hand side are the CX scores while the right-hand side are the rescaled gas values from V1.

Table 2. Average customer experience and average gas of the touchpoints (TP), comparing including all available data and with filtering only the values that have a CX score and a gas value in the game.

TP	Avg Gas (All)	Gas (1–5, All)	CX (All)	Diff. (All)	Avg Gas (Filt.)	Gas (1–5, Filt.)	CX (Filt.)	Diff. (Filt.)
T0	1.2	3.5	3.9	0.4	2.5	3.7	3.9	0.2
T1	2.0	3.6	4.5	0.9	2.3	3.7	4.5	0.8
T2	5.4	4.0	4.9	0.9	10.3	4.2	4.9	0.7
T3	-4.2	3.0	4.7	1.7	15.8	5.0	4.3	0.7
T4	7.2	4.1	4.2	0.1	9.1	4.3	4.2	0.1
T5	6.9	4.1	4.4	0.3	11.2	4.5	4.6	0.1
T6	11.8	4.6	4.7	0.1	14.5	4.9	4.8	0.1
T7	5.8	4.0	4.5	0.5	12.2	4.6	4.6	0.0
T8	15.8	5.0	4.4	0.6	15.8	5.0	4.4	0.6

Investigating touchpoints scoring less than 4. We examined the touchpoints where the customer experience (CX) score was less than 4. The results are presented in Table 3, which shows the CX score and gas value for each low-scoring touchpoint, along with the customer who provided the score. The "Difference" column indicates the absolute difference between the two scores. When allowing for a maximum difference of one point, the gas value aligns with the CX score in 3 out of 20 touchpoints (15%).

Table 3. Comparison of customer experience score and gas across touchpoints scoring less than 4.

Customer - Touchpoint	CX score	Gas (1–5)	Difference
C2 - T0	1	4	3
C2 - T1	1	4	3
C3 - T0	1	4	3
C3 - T4	3	5	2
C6 - T8	1	5	4
C8 - T0	1	4	3
C8 - T1	3	4	1
C8 - T4	1	3	2
C8 - T5	1	5	4
C8 - T6	2	5	3
C8 - T8	3	5	2
C10 - T0	3	5	2
C12 - T0	2	4	2
C12 - T1	3	4	1
C12 - T4	3	5	2
C12 - T6	3	5	2
C12 - T7	1	5	4
C16 - T4	3	5	2
C22 - T4	3	3	0
C23 - T8	3	5	2

Investigating Journeys Firstly, we compared journeys with negative average gas in the user journey game against the completion status and average CX scores obtained through the CJA. Customers with negative gas values who did not complete the broadband installation were also characterized by missing CX feedback. As a result, these journeys were excluded from the comparison of average gas and CX scores. Figure 8 illustrates the result of sorting on the difference between the average CX score (left-hand side) and the average gas translated into the 5-point scale (right-hand side) we obtain the values with the gas values from V1. The CX score table uses the same gradient color scale as in Figure 7. From that we perceive that Customers 22, 12 and 8, are the ones where the difference is larger than 1. Investigation in the CJA revealed that Customer 22 went to a physical store to successfully install the MBB product – classified as a specific deviation in the dataset, and therefore not modelled in the games.

Customer (ID)	T0	T1	T2	T3	T4	T5	T6	T7	T8	CX Average	Diff.	Gas (1-5) Average	T0	T1	T2	T3	T4	T5	T6	T7	T8	Gas Avg.
22		5	5		3	5				4,5	2,5	2	1,75	1,36	-24		-4,2	-24	-24	-24		-14
8	1	3			1	1	2	2	3	1,9	2,34	4,2	1,75	1,36	7,52		-2,6	15,8	15,8		15,8	7,92
12	2	3	4		3	5	3	1	5	3,3	1,35	4,6	1,75	1,36	15,8		15,8	15,8	15,8	15,8	15,8	12,2
3	1			5	3		5		4	3,6	0,9	4,5	1,75	1,36	7,52	15,8	15,8		15,8		15,8	10,6
13	5	5	5	3	5	5	5	5	5	4,8	0,68	4,1	1,75	1,36	7,52	15,8	15,8	-4,2	-4,2	15,8	15,8	7,27
23	5	5	5	5	5	5	5	5	3	4,8	0,68	4,1	1,75	1,36	7,52	15,8	15,8	15,8	15,8	-24	15,8	7,27
5	4	5	5	5	5	5	5	5	5	4,9	0,59	4,3	1,75	1,36	7,52		-2,6	15,8	15,8	15,8	15,8	8,91
18	5	5	5				5		5	5,0	0,5	4,5	1,75	1,36	7,52		15,8	15,8	15,8	15,8	15,8	11,2
19	5	5	5		5	5	5	5		5,0	0,5	4,5	1,75	1,36	7,52		15,8	15,8	15,8	15,8	15,8	11,2
2	1	1	5		5	5	5	5	5	4,0	0,4	4,4	1,75	1,36	15,8		-2,6	15,8	15,8	15,8	15,8	9,94
9	5	5	5				5	5	5	5,0	0,4	4,6	1,75	1,36	15,8		15,8	15,8	15,8		15,8	11,7
1	5	5	5		5	4	5	5	5	4,9	0,38	4,5	1,75	1,36	7,52		15,8	15,8	15,8	15,8	15,8	11,2
15	5	5	5		5	5	5	5	4	4,9	0,38	4,5	1,75	1,36	7,52		15,8	15,8	15,8	15,8	15,8	11,2
7	5				4	5	5	5	5	4,8	0,23	4,6	1,75	1,36	15,8		15,8	15,8	15,8	15,8	15,8	12,2
14	5	5	5	5	5	5	5		5	5,0	0,2	4,8	1,75	15,8	15,8		15,8		15,8		15,8	13,5
16	5				3	5	5	5	5	4,7	0,17	4,5	1,75	1,36	7,52		15,8		15,8	15,8	15,8	10,6
6	4	5		5	5	5	4	5	1	4,3	0,15	4,4	1,75	1,36	15,8		-2,6	15,8	15,8	15,8	15,8	9,94
10	3				4	5	5	5	5	4,5	0,1	4,6	15,8				-4,2	15,8	15,8		15,8	11,8
4	5	5	5	5	5	1	5			4,5	0	4,5	1,75	1,36	7,52		15,8		15,8	15,8	15,8	10,6

Fig. 8. Comparison of average CX (left-hand side) and average gas (right-hand side) for all journeys with available CX scores from the CJA, sorted in descending order of difference.

Moreover, we see that there is no CX score recorded from T5 and onwards, where the gas in T6 and T7 is heavily negative. For Customer 12, the CJA captured that he ended up cancelling the product after he had successfully installed it, and that he was, amongst other, frustrated that the sales agent convinced him to try MBB as a remedy for his slow connection, but did not improve it. The CJA also captures that Customer 8 had many specific deviations, and these are reflected in her qualitative pain-points. The pain-points of these two customers, along with the specific deviations, are not captured through the game approach.

The accumulated gas accurately reflects the customer experience in 84.2% of the journeys in V1 with the inclusive criteria on less than 1 point in acceptable difference. Replicating the same for V2, some values change slightly, but the same three customers remain over the inclusion limit.

There are several individual journeys we chose to highlight and investigate in more detail, as shown in Table 4. Since the dataset contains many specific deviations—and we only included D1 (failure to install the MBB product)—we wanted to investigate the journeys that contain no deviations, apart from differences in the order of touchpoints. Customers 2, 13, and 23 meet this criterion, and their journeys are similar in both V1 and V2. As shown in Table 4, the difference between CX and gas is less than 1. The results also show that the customer with the highest accumulated gas—Customer 14—has the highest CX

score. Finally, even for the customer whose gas values differ the most between V1 and V2, the variation remains minor.

Table 4. Overview of the average gas compared to the average CX score for selected journeys.

Game Version	Selection Criteria	Customer (ID)	Avg Gas (1–5)	Avg CX (1–5)	Difference
V1 & V2	No journey deviations	C2	4.4	4.0	0.4
		C13	4.1	4.8	0.7
		C23	4.1	4.8	0.7
V1	Highest accumulated gas	C14	4.8	5.0	0.2
V2		C10	5.0	4.5	0.5
V1	Shortest strategy	C10	4.6	4.5	0.1
V1	V1 and V2 most unlike	C10	4.6	4.5	0.1
V2			5.0	4.5	0.5

Investigating journeys scoring less than 4. The customers scoring less than 4 on their overall journey are depicted in Table 5, noting that there is no customer experience data on the four customers that did not succeed in installing the MBB product. From the table we can see that the data only consists of four journeys, where gas could reflect the CX score 2 out of 4 times (50%).

Table 5. Comparison of CX score, Gas value, and their difference.

Customer	CX score	Gas (1–5)	Difference
2	4,0	4,4	0.4
3	3,6	4,5	0.9
8	1,9	4,2	2.3
12	3,3	4,6	1.3

5 Discussion

5.1 Inferring Experience from Gas

With the inclusion criteria of 1, gas could reflect the CX score of single touchpoints 79.4% of the time and 84.2% on the journey level. However, there is little variations in experience scores in the MBB dataset. As the result show, most of the touchpoints are highly rated – between 4 and 5. For the few touchpoints and journeys scoring below 4, the ratings do not consistently correspond with the gas values, as shown in both Table 3 and Table 5. Since gas, when converted into the 5-point scale, also tends to fall between 4 and 5, the instances where experience scores are lower are particularly noteworthy. To better assess whether gas also

can capture poor customer experiences, further research is needed—ideally using a larger dataset and a more complete customer experience dataset.

Some of the observed mismatches between gas and customer experience can be explained by factors that lie outside of the scope of the weighted games. For example, certain pain points—such as feeling pressured into buying the product—are not data-driven and could be subjective, and therefore not reflected through the gas values. Other issues are more data-driven, but not yet within the scope of the user journey game in this paper, such as other types of deviation—calling customer service, failing to get the correct PIN-code. These findings suggest that a significant portion of the customer experience lies outside the observable sequence of touchpoints. Future research should investigate how to incorporate and model these deviations in the user journey games.

Moreover, there are several challenges related to comparing the CX scores with the gas values. A key challenge is that some of the customers left the experience score blank for some of the touchpoints. To account for missing data, we tested the exclusion of gas values that lacked corresponding CX scores, as shown in Table 2. This approach appeared to improve the correlation between gas and CX for the average touchpoints. However, it reduced the size of the dataset and made the analysis less comprehensive, representing a key limitation of the study. Future work should aim to improve data collection processes to ensure more complete customer feedback, which would support more robust correlation analysis.

Another limitation concerns the method used to compare CX scores and gas. In this study, we applied a linear min-max normalization strategy to translate gas into a common 5-point scale. However, because gas incorporates entropy—which is not linear by nature—this linear mapping may not fully reflect the relationship between the two metrics. Future research should explore non-linear mapping strategies to determine whether they offer better alignment and help establish a more meaningful common scale between gas and CX. A final point of discussion concerns the extent to which the users’ experience can truly be captured. Even when CX scores are collected, they may not fully reflect the actual journey due to various external influences. For instance, in our dataset, several customers who encountered challenges—such as needing additional assistance with MBB product installation—still assigned high scores to the corresponding touchpoints. A notable example is Customer 5, who rated almost all touchpoints with top scores, despite the CJA revealing issues such as lack of cost transparency, installation difficulties, and prolonged support wait times. Showcasing what is also discovered through the CJA, that customers can rate the touchpoints as "good" even though they encountered problems, a general trend when asking customers to rate experience[16]. This discrepancy can also suggest that other outside factors can influence the experience ratings, such as the mood [12].

5.2 Comparison of CJA and Weighted User Game Approach

CJA and the weighted user game approach can supplement each other as they offer different complementary strengths as described in Table 6. As seen in Section

Table 6. Summarizing table of the two approaches.

	CJA	User Journey Games
Insights	Single journey insight or simple holistic insight.	Aggregated insight with a historical aspect. Possible forecasting capabilities
Pain-points and deviations	Manual. Accurately represented based on actual user feedback	Automated. Estimated through aggregated behavior and modeled outcomes
Data handling	Only handles a limited number of journeys. Can handle a sparse dataset	Can analyze large datasets. Needs larger amount of data
Level of automation	Manual	Automated
Method	Qualitative	Quantitative
Touchpoint Coverage	Across systems	Event logs or across systems applying it on customer journeys
Timing	Included	Excluded

4.3, they provide overlapping insights, but also contributes unique value—CJA offers depth at the single end-user level, while the user game approach supports broader, aggregated journey analysis. It identifies a shorter strategy—journey – through the model checker, often interpreted as the most “efficient” path. The results shows this path is not among the highest-ranked in terms of customer experience— though it still performs reasonably well, with an average CX score of 4.5. Qualitatively, the shorter strategy appears feasible—for example, if the installation guide (T6) states that a SIM (T4) and PIN (T5) are required, a customer who has not received either may infer they need to wait, even without explicit instructions (T1, T2, T3). However, since only one customer followed this path, it presents a major limitation regarding the viability of the shorter strategy. A larger dataset could potentially include more users who take the same journey and provide additional CX scores for further analysis.

CJA, on the other hand, is a qualitative, manual process that can provide rich insights into single customer journeys, discussing their pain-points, thoughts, and collecting customer experience across touchpoints— including those that span across systems and leave no digital trace. While CJA delivers a comprehensive view, its holistic insights can be hard to extract unless issues are plainly visible. In contrast, the user game method is quantitative and scalable, but requires a larger number of journeys for meaningful results. Importantly, the weighted game approach has the potential to be used for forecast modeling as by analyzing possible actions from a given state, it can suggest how service providers might steer customers toward successful outcomes.

However, a key limitation of the game-based approach is its lack of temporal dimension and expressiveness that CJML explicitly incorporates. Timing of touchpoints is a critical component of a customer journey. The service experience

is shaped not only by what happens, but when it happens. For example, a confirmation message is expected immediately after a purchase is completed; any delay may introduce uncertainty or dissatisfaction. The duration of individual steps and the latency between them can significantly affect the end-user. Therefore, integrating temporal aspects into game-derived modeling would strengthen its validity. A potential way of doing it could be to incorporate deviations that capture significant timing discrepancies between expected and actual touchpoints. However, this remains an area for future research. Overall, combining the qualitative depth of CJA with scalable analytics of user journey games offers the potential for insights at both individual and aggregated journey levels.

6 Conclusion

The objective of this paper was to assess the two analysis approaches, Customer Journey Analysis (CJA) and a weighted game approach on CJML journeys, exploring the combination of these two approaches could be integrated, and whether gas could be used as an indicator for customer experience. Based on the inclusion criteria, gas could reflect the customer experience score of single touchpoints 79.4% of the time and 84.2% on the journey level. At first glance, gas may appear to be a useful indicator, showing higher accuracy at the journey level. However, for journeys and touchpoints scoring below 4, the gas values often failed to reflect the experience scores, which weighs negatively on its reliability in inferring experience. Given the exploratory nature of this research, several limitations remain that should be addressed in future studies to draw firm conclusions about this correlation. These include not only constraints related to the research design—such as the need for more comprehensive datasets with a greater number of journeys and more complete customer experience data—but also conceptual challenges in applying game-based approaches to customer journeys—such as the lack of temporal modeling. Still, the comparison method presents a useful direction for future work with more comprehensive datasets. Moreover, combining the qualitative depth of CJA with scalable analytics of user journey games offers the potential for insights at both individual and aggregated journey levels, and can, in the future, help advance the development of automating the journey analysis process on exhaustive customer journeys.

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