Customer Intelligence in the Cultural Sector: The Case of a Quebec Museum

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Abstract. The COVID-19 pandemic has heightened the importance of digital strategies and data use in museums, transforming how they deliver services and engage with audiences. As a result, museums have adapted to new audience profiles and digital methods of organizing and accessing collections to thrive in the post-pandemic era. These organizations have thus generated more and more data without the human and technological resources required to perform the analyses. In addition, the lack of consensus regarding an analytical framework in the academic literature complicates the implementation of customer intelligence among Small and medium-sized enterprises (SMEs) and non-profit organizations. To respond to this challenge, this study proposes a customer intelligence process for implementing customer intelligence around four stages: Acquisition - Commitment - Experience - Lifetime Value, associated with three states: Data - Analysis - Key Performance Indicators. The POP Museum, in the Province of Québec, Canada, which has developed online exhibitions and currently uses social media to better get to know its customers, follow their customer journey and ultimately develop customer intelligence, is presented as a case study.

1 Introduction

The COVID-19 pandemic has fundamentally shifted how data is perceived, utilized, and valued across the cultural sector, especially within museums, underscoring the critical role of strategic foresight and digital preparedness in transitioning to digital service delivery. This transformation has led to a shift in digital engagement and data management practices within museums, making digital methods for organizing and accessing collections more crucial. Additionally, the increase in online engagement has altered traditional audience profiles, prompting museums to adapt to new engagement strategies to ensure their survival and success in the post-pandemic landscape [1].

According to UNESCO [2], an estimated 104,000 museums currently operate in 87 member countries. In 2020, a large proportion (43%) was forced to temporarily close their doors, but for variable periods, because of the health measures imposed due to the COVID-

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19 pandemic. Museums have seen a decline in both state funding and attendance. For the 1,391 museums in Canada, this drop in public attendance is in the 91%-100% range according to Statistics Canada in 2019. Life-saving solutions have been implemented to minimize the impact of the closures, such as a shift to digital technology as a tool to distribute and communicate the museum offerings. The hybrid offering by certain museums is an important asset to share culture and inject entertainment value and "certain sites no longer hesitate to use innovative and 'living' museography and scenography" [3-5]. Indeed, the pandemic has forced cultural and tourism organizations to accelerate their digital transition [6].

Consequently, the tourism sector is characterized by the rapid exploration and exploitation of knowledge based on the relationship between the ability to produce knowledge, the mechanism for its distribution, and the capability of the different stakeholders to absorb the knowledge and gain intelligence from it [7]. In this spirit, the POP Museum in Trois-Rivières (in the Province of Québec, Canada) showcases a collection of Québec folk art in a dynamic, interactive, and immersive manner, through original exhibitions by using customer intelligence to guide decisions, while improving the organization's performance [8]. The work of McAfee et al. [9] has shown that artificial intelligence allows user businesses to increase profits by 6% on average compared to their competitors and make better decisions based on data, and big data, in particular [10].

In particular, a business is not "smart" if it does not make any adjustments considering the information collected from its customers [12]. In the cultural sector, organizations such as the POP Museum attempt to map out customer journeys by identifying the key touch points at each step, as they present interactive opportunities for potential customers to engage with cultural organizations [13]. As an extension of the work mentioned above, the purpose of this article is to propose a customer intelligence process for the implementation of customer intelligence based on the various stages in the customer journey. Following a review of the literature on the main stages in the customer journey, we present the case of the POP Museum and discuss the results.

2 Literature review

2.1 Customer Journey

The customer journey is a process that focuses on the point of view of the customer [14] and that represents a cyclical sequence of interactions between customers and organizations [15]. Although the customer journey is of strategic importance for organizations, there is no consensus on its definition, as shown in Table 1.

Table 1. Presentation of Various Customer Journeys.

Steps	Authors	Advantages	Inconveniences
(AIDA) Attention, Interest, Desire, Action	Lewis [16]	One of the first simple models of the hierarchy of effects.	The customer journey does not follow a linear approach, which was invalidated by other studies.
Needs, Information seeking, Alternative evaluation, Purchase and post-purchase	Wolny & Charoensuksai [17]	Conventional model that makes it possible to analyze the customer journey both online and offline.	The involvement phase and the notion of risk receive little attention in this model.

Consider, Evaluate, Buy, Enjoy, Advocate, Bond, Consider...	Edelman & Singer [18]	Cyclical approach that follows two pathways based on the decision loop or the loyalty loop.	The steps proposed are not always followed in a linear fashion by consumers.
(4A) Aware, Attitude, Act, Act Again	Kartajaya et al. [19]	Mnemotechnical approach inspired by the AIDA (linear) model. Applies to both consumers and organizations.	The customer journey is not necessarily linear.
Prior experience, Pre-purchase, Purchase, Post-purchase, Future experience	Lemon & Verhoef [20]	Simple model to analyze with three main stages while addressing a cyclical approach.	Little differentiation between the various stages.
PROPE (Problem, Research (information), Options, Participation, Evaluation)	Trespeuch et al. [21]	Linear mnemotechnical model that includes participation.	The consumer experience cannot be limited to the purchase. Weak integration of the cyclical aspect of the customer journey.

Based on the common points shared among the customer journeys presented above, we propose the following four stages.

The first concerns customer **acquisition**. The AIDA (Attention, Interest, Desire, Action) model appears to still be relevant as the first step is to attract the consumers' attention, even though this step is increasingly difficult given the limited ability of individuals to react to ever more numerous stimuli [19].

Commitment is the 2nd stage and answers the question "*How can the conversation with the consumer be maintained?*" This pre-purchase stage incorporates the attitudes taken up by [19], already present in the model put forward by [22]. It is also at this stage that consumers evaluate the alternatives and can eventually choose a competing or substitute product to meet their needs.

The third stage corresponds to consumer **experience**, based on the behavioural component of the model introduced by [23]; transaction and participation in the sense of co-creation of value [24, 25] are also included in this stage.

The fourth stage, **lifetime value**, corresponds to the cyclical, iterative aspect found in the models put forward by [18, 20]. A given experience is indeed rarely isolated from the past experiences of a consumer. It, therefore, appears relevant to consider the customer journey from a holistic perspective by considering all these consumer data [26].

2.2 Customer intelligence

This study refers to the definition of customer intelligence proposed by [26]: "*Customer intelligence is the ability to acquire knowledge and skills from massive data through customer analytics and then apply them to the process of creating, communicating, delivering, and co-creating to offer value*." This definition is aligned with the model presented in Table 2 and follows the rationale of Collection (Data) – Processing (Analytics) – Exploitation (KPI).

The benefits of customer intelligence are numerous: i) A better understanding of consumer behavior and the ability to predict their needs [27]; ii) An ability to estimate the lifetime value of customers [28]; iii) An improvement of satisfaction rate and customer experience [29]; and iv) A precious opportunity to leverage the “7 Ps” of service marketing [11].

The development of customer intelligence consists of recognizing customer needs, determining a product or service, optimizing communication, and responding to the delivery of services and products [30,31]. However, simply having massive data does not guarantee better decisions. Businesses need an integrated system to collect, analyze, and use the data [32].

3 Methodology

A case study research method was used, which is an appropriate method for answering "how" and "why" types of research questions [33]. A single case was analysed in this study, i.e., the POP Museum in Trois-Rivières, in the Province of Québec, Canada. The current management operates this museum using an entertaining and interactive hybrid approach for both school audiences and young families.

Data collection. This museum uses various data to support its marketing decisions. Secondary data were collected in this study by interviewing the Marketing director and her team and by performing document analysis. Document analysis involves systematically reviewing and interpreting various types of documents, especially the different business reports and their data related to the case. Interviews allow the researcher to gather in-depth, firsthand information directly from key stakeholders and participants involved in the case [33]. Customer intelligence begins with data that can be categorized into four main types: demographic, behavioural, transactional, and psychographic [8][11][26]: i) *Demographic data* provide information about Who the customers are, such as their age, gender, income, marital status, occupation, and location. This data can be obtained from sources like government statistics, CRM systems, and social media; ii) *Behavioural data* reveal How customers interact on websites, mobile apps, and social platforms. This data offers a quick snapshot of customer behaviours and activities; iii) *Transactional data* show What customers have purchased. This information can be gathered from various sources, including transaction records, sales reports, billing data, and CRM systems; and iv) *Psychographic data* explain Why customers make purchases. This involves integrating demographic, behavioural, and transactional data to uncover the motivations and reasons behind buying decisions.

Data processing. Data preprocessing is a critical step in customer intelligence that includes data integration, data transformation, and data reduction [11]. The process begins with data integration, which involves collecting and consolidating customer data from various selected sources. This raw data is then cleaned to handle missing values, reduce noise, and eliminate any duplicate or erroneous information. Next, data transformation occurs to normalize the data and ensure all variables are on a standard range. This may also involve creating new derived variables through mathematical functions and combining or restructuring the existing data. Finally, data reduction techniques are applied to decrease the number of attributes and the overall volume of the dataset. This is essential, as processing a large, unwieldy dataset can be computationally intensive and impractical. By systematically executing these data preprocessing steps, the customer data is transformed into a clean, consistent, and manageable format. This prepares the data for further analysis and the generation of meaningful customer intelligence.

Data analysis. Data analysis encompasses a progression of analytics that transform raw customer data into valuable business insights [11]: i) *Descriptive Analytics*: This initial stage focuses on exploring historical data and converting it into actionable information. Techniques used in descriptive analytics include business reporting, descriptive statistics, regression modelling, and data visualization. These methods help organizations understand what has happened in the past; ii) *Predictive Analytics*: Building upon the descriptive foundations, predictive analytics leverages quantitative techniques like statistical modelling, regression analysis, and various machine learning methods. These techniques aim to predict future outcomes and uncover insights about customers. Machine learning approaches such as clustering, classification, regression, association analysis, and sequence discovery can all provide forecasts and predictions; and iii) *Prescriptive Analytics*: The final stage involves converting the predictive knowledge into prescriptive intelligence that can guide complex business decisions. Prescriptive analytics utilizes techniques like optimization and simulation to generate recommended actions and strategies based on the customer insights gleaned. This empowers organizations to make more informed, data-driven decisions.

4 Results

In general, the outcomes of the study could be different types of customer intelligence [8][11][26]. *Product-aware intelligence* demystifies what customers like and develops products/services based on their needs to promote product/service innovation in optimizing product/service features and characteristics along with providing a unique and remarkable experience for customers. *Customer DNA intelligence* aims at identifying, targeting, and positioning customers for personalized services so that enterprises can divide a business market into subgroups of customers with similar characteristics and develop into customer profiles. *Customer experience intelligence* empowers enterprises to provide better services by understanding journeys, behaviours, engagement, and co-creation of customers to demystify value, resources, and engagement forms. *Customer value intelligence* works toward maximizing customer value for enterprises so that enterprises can predict the total monetary value that customers are expected to spend for an enterprise during their lifetime.

Concerning the case study, this section presents the customer intelligence process based on the different types of customer intelligence, including the stages of customer acquisition, customer commitment, customer experience, and customer lifetime value [34]. As illustrated in Table 2, each activity is clarified with the required data sources, analytical techniques, and key performance indicators (KPIs) related to customer intelligence.

Table 2. Customer Intelligence Process.

	Acquisition	**Commitment**	**Experience**	**Lifetime Value**
Data	Demographic data (age, gender, place of residence, etc.)	Psychographic data (lifestyles, preferences and habits, etc.)	Behavioral data (navigation history, items added to cart, etc.)	Transactional data (orders, purchases, revenue, etc.)
Analytics	• Clustering • Classification	• Classification • Regression • Clustering	• Classification • Association • Clustering • Sequence discovery • Regression	• Sequence discovery • Association • Classification • Prediction • Regression
KPIs	• Visits: 2,163 web visits/month • FB reach: 18,185/month • Gender: % ♀ Google: 45.85 / % ♀ FB: 73.70	• Bounce rate: 70.35% • Session length: 2 min. 10 sec. • Likes/shares/subscribers/comments	• Customer churn rate: 49.5% • Customer retention rate (new	• Customer lifetime value (in progress) • Cost per lead (in progress)

	• Age: %25-34 FB: 23 / %35-44 FB: 32.4 / %45-54 FB: 18.7 • Cities: Trois-Rivières: 23.4%; Montréal: 10.8%; Québec: 6.5%	(294/11/0/28 per month)	users/Users): 98% • Trip Advisor score: 4/5 (101 votes) • Google score: 4.4/5 (230 votes)	• Average order value: $23.09

5 Discussion

Customer acquisition. Customer acquisition relies on customer *demographic data* to determine age, gender, occupation, place of residence, income, and marital status [28, 35]. With data, businesses can build customer profiles and choose the most profitable segment.

Thus, analytical techniques such as clustering and classification are applied to identify interesting customer segments with similar profitability [28, 36]. Classification mining techniques include neural networks, decision trees, the Naïve Bayes method, support vector machines, shopping cart analyses, genetic algorithms, and if-then rules [36, 37]. On the other hand, the most common cluster extraction techniques are K-means, the Naïve Bayes method, RFM (recency, frequency, monetary value) analysis, shopping cart analyses, neural networks, and self-organizing mapping techniques. Customer acquisition activity focuses on generating traffic toward websites and social media as well as other sources of traffic [36]. As such, important KPIs include several *visits, total reach, total impressions*, and *social share of voice* [38, 39]. The *number of website visits by traffic source* is a useful KPI to examine customer traffic. This KPI allows executives to see a breakdown of all sources such as organic search, paid search, campaign website, display advertising, emails, or social media [40]. The POP Museum has access to various data from Google Analytics, Facebook Insights, and invoicing systems. Based on the POP Museum's data sources, several KPIs are developed to acquire customers, including *daily organic reach, daily total reach*, and *number of website visits by traffic source*. For example, the *number of website visits by traffic sources* indicates that 66.9% of users are from Google search, 17.6% are direct access, 7.6% are from Facebook, etc.

Customer commitment. Customer commitment aims at personalizing marketing strategies based on *psychographic data* that reveals information about customer lifestyles, preferences, and habits [27, 41]. Businesses normally develop customer profiling, campaign management analyses, credit scoring, referral systems, or loyalty programs to increase customer commitment and maintain long-term relationship [42, 43].

Thus, various data mining methods are applied to support these activities such as classification, association, clustering, sequence discovery, and regression [36]. As a result, association rules, decision trees, neural networks, logistic regression, and genetic algorithms are increasingly attracting the attention of researchers [36, 44]. To get an idea of how visitors interact on web pages, executives look at the bounce rate as well as the average session length [45]. The longer the average session length, the more engaging the content and structure of the website [45, 46]. In addition, the number of pages per session indicates the degree of customer engagement [39]. On social networks, executives identify KPIs that reveal user engagement, such as the number of *likes/shares/subscribers/comments* [47]. Concerning the POP Museum website, *positive and negative comments by date, daily likes by source, bounce rate, average session length*, and *pages per session* are taken into consideration.

Customer experience. Customer experience examines *behavioural data* that can be acquired from social media, websites, and connected devices [11]. Customer interactions on websites and mobile devices disseminate information about customers, such as their browsing history, additions to favourites, or items added to their cart [48][49].

Customer experience focuses on customer satisfaction by improving the value, design, and orchestration of the customer journey through constant innovation, from pre-purchase to post-purchase [29]. Increasing value includes product/service improvements, product sustainability and innovation, and services and direct delivery to customers. Many companies are upgrading technology (mobile apps) and infrastructure to increase customer satisfaction with the products and services offered as well as the delivery process [50]. Customer experience on a website is reflected in KPIs with indicators such as the *customer churn rate* and *customer retention rate* [47]. To gain better insights into customer web experience, executives can explore the *net promoter score* and the *customer satisfaction score* by surveying customers on the website [27, 51]. As with most cultural organizations, the POP Museum is not yet ready to deliver a memorable customer experience, but is currently working toward achieving this goal.

Customer lifetime value. Customer lifetime value involves *transactional data* that can be found from various sources such as transaction records, sales reports, invoicing records, and customer relationship management systems [44, 48]. It maximizes value creation for businesses by covering three main perspectives: upselling/cross-selling, customer lifetime value, and shopping cart analyses [36, 42].

Sequence discovery and association are the data mining methods that support up-selling/cross-selling and shopping cart analyses. More specifically, association rules and neural networks are the most common data mining techniques [36]. To estimate customer lifetime value, data scientists apply various data mining models, including classification, clustering, prediction, and regression [27, 28]. As such, the corresponding analytical techniques are neural networks, Bayesian network classifiers, association rules, linear regression, survival analysis, and the Markov chain model.

Customer lifetime value activity is also reflected in other KPIs such as *customer lifetime value* and *cost per lead* [52]. *Customer lifetime value* defines the total value of a customer while cost per lead measures the cost of acquiring new customers. Another important KPI to consider is the *average order value* [46], which measures sales per order rather than sales per customer [39]. As a result, not only does it improve financial performance (i.e., sales, return on investment), but it also refines marketing strategies by segmenting customers based on the average value of their orders.

Measuring customer lifetime value is a difficult task for cultural organizations in general, and for the POP Museum in particular, as it involves identifying the touch points where the customer creates value. Once the POP Museum has achieved customer experience activity, customer lifetime value can be measured.

6 Conclusion

The COVID-19 crisis has severely affected cultural organizations, in particular, and the tourism sector, in general. It is, therefore, more important than ever for museums to understand the behaviour of their visitors to better serve and retain them. The main contribution of this study is the creation and application of a customer intelligence process for intelligent marketing in four steps: *Acquisition – Commitment – Experience – Lifetime Value* associated with three states: *Data – Analysis – Key Performance Indicators*.

From a managerial standpoint, museum managers need to follow the experience of their online visitors. Understanding the online customer journey can help them design strategic touch points to create trust and improve their relationship with visitors. From a theoretical standpoint and further to the work of [35], the proposed customer journey analytical framework presents an overview of how businesses, and cultural organizations, in particular, can become smart businesses.

Until now, practically no studies focused on customer intelligence in the cultural sector [53]. As a result, this study can be viewed as a pioneering effort; one that fills a significant gap in marketing and the cultural sector. Ultimately, the generic process of applying customer intelligence opens new avenues for research for both academics and practitioners. A potential limitation is the relationship between the process, outcomes, and categories of customer intelligence in the context of SMEs which could be addressed by future studies.

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