In-Store Customer Analytics – Metrics and Maturity Scenarios for the Collection of Physical in-Store Customer Data for Retail

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Abstract While collecting and analyzing customer data via the web browser (Web Analytics) is very common in online-retail, stationary retail outlets have so far tended to neglect to collect and assess data of customer visits to their stores (In-Store Customer Analytics) and have instead tended to focus on analyzing transaction data. Yet for online retail, it is the analysis of customer data prior to the transaction that has been the most influential tool for the further development and improvement of services, in particular the optimization of the landing page and conversion optimization. Thus it can be assumed that the analysis of customer visit data offers a similar potential to improve services and conversion rates for stationary retail. This paper offers a systematic assessment of the measurable components of in-store customer metrics based on an extensive literature review and furthermore provides a matrix for maturity assessment for a number of key technologies that are available for in-store customer analytics.

Keywords In-Store Customer Analytics, Metrics, Customer Data Maturity Matrix

1 Introduction

Customer data analysis (Web Analytics) is an established practice for online-retail [DFK02]. The customer data collected via the web browser is compared to the transaction data stored in the shopping system and thus the transactions are compared to the potential transactions (visitors to the website) in the so-called conversion rate. Web-Analytics is a method of using the browser data received in order to improve the structure, the setup of the landing page and the pricing as well as the offers of an online shop in such a way as to increase sales. This online analysis is an essential part of virtually all online platforms [DML11]. In contrast to this, customer data for in-store visits remains virtually uncharted territory[Ge14]. Even though strategies for analyzing visitor data have been developed and analyzed for decades (e.g., via manual counting, using test customers, using eye tracking or using modeling systems such as blueprinting) [Gr68] [BD95] [NJ99] [Bi10], (partly) automatized assessment and analysis of customer data (In-Store Customer Analytics) has not really become an established practice. Instead, retailers and researchers continue to concentrate on analyzing transaction data and thus neglect the opportunity to expand their analysis horizon to include in-store customer data that is not covered by the transactions [BK12] [Su15]. One reason for this reluctance to engage in new analysis methods may be due to the fact that retail is experiencing a major change, in which the search for new solutions is high-cost, error-prone and difficult to integrate into the existing infrastructure [GC05]. A number of technologies are available for collecting and assessing in-store customer data, though these have different degrees of maturity. What is missing, however, is a systematic evaluation of the basis for in-store customer data analytics that is not biased towards one particular technology. Thus it is the aim of this paper to provide a systematic overview of the current state-of-the-art of In-Store-Customer Analytics based on a structured literature review, in order to answer the following research questions:

RQ1: *What kinds of technologies are available for the collection and analysis of in-store customer data?*

RQ2: *What type of customer metrics can be collected in-store?*

RQ3: Which technologies provide which type of customer metrics analysis?

This study provides an independent assessment of the different data collection technologies and then concentrates on the possible metrics analysis that can be harvested from them. The interface between in-store customer data and in-store transactions are deliberately not taken into account, in order to focus on in-store customer data. The paper has the following structure: After this short introduction, the first part of Section 2 looks at the classification of Web Analysis Metrics (as established by the Web Analytics Association [We16]) in order to derive a classification for in-store customer metrics based on the Web Analytics categories. The second part of Section 2 then presents the current research on customer data analytics based on a systematic literature analysis and also lists and classifies all technologies available to date and their respective analysis range. Section 3 is a detailed discussion of the data collection technologies, looking at their individual technical development and assessing their performance potential. Section 4 selects a number of key metrics from the in-

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store customer metrics assessed earlier, in order to reduce the complexity in such as way as to be able to create a matrix to assess their maturity and thus provide a structured overview of the available data collection technologies and the metrics they can supply. Section 6 discusses the resulting implications of the maturity assessment for the practical implementation of In-Store Customer Metrics, which is then concluded in Section 7 with some key recommendations and an outlook into the future of in-store retailing.

2 Literature Review

The literature review provided here is divided into two sections. The first part looks at Web Analytics and the Web Analysis Metrics, in order to develop categories that make sense for a classification of in-store customer metrics. The second part is a structured literature review, based on the categories established in the first part, which are used for a systematic literature review of data collection technologies.

2.1 Web Analysis Metrics

While in-store customer data analytics is still virtually uncharted territory, Web Analytics is very well established and already very well classified, the existing metrics have been standardized and categorized [TB03] [Gu13]. The organization responsible for the classification, the Web Analytics Association (WAA)[We16] publishes a collection of categorized Web Metrics with their definitions on their website. These are accepted as a global standard. The WAA distinguished two different types of metrics, ‘Count’ is a directly measured number (e.g., the number of visitors to a website) and ‘Ratio’ is a derived metric, that can be calculated via other metrics (e.g. the average time of a visit to an online shop). The 22 metrics listed by the WAA are classified into six categories, not all of which can be transferred to our In-Store-Customer Metrics classification system.

1. Building Block	2. Visit Characterization	3. Visitor Characterization	4. Engagement	5. Conversion	6. Miscellaneous
Page	Entry Page	New Visitor	Page Exit Ratio	Conversion	Hit
Page View	Landing Page	Returning Visitor	Single Page Visits	Conversion Rate	Impressions
Visits	Exit Page	Repeat Visitor	Bounce Rate		
Unique Visitor	Visit Duration	Visitor Referer	Page views per Visit		
Event	Referer	Visits per Visitor			
	Session Referer	Recency			
	Click-Through	Frequency			
	Click-Through-Rate				

Table 1 Web Analytics Categories and Metrics [We16]

As the category Conversion is a cross-reference between customer data and transaction data, this will not be studied in this paper. The metrics of the category Miscellaneous cannot be transferred to the in-store situation and will therefore also not be studied here. From the four other web metrics categories, two in-store metric categories can be derived.

1. Location Metrics of the category ‘Visit characterization’
2. and behavior metrics in the category ‘Engagement’.

The Web analytics categories Building Block and Visitor Characterization also show that the derived categories have to be expanded to a further dimension as to identification, as these categories contain individualized and person-specific location and behavior metrics. For metrics such as ‘New, Returning or Repeat Visitor’ a customer identification is needed, while metrics such as ‘Visit’ can be collected as long as one individual, but not identified, visitor can be distinguished.

2.2 In-Store Customer Analysis-Metrics

The following systematic literature review, based on journal papers and conference proceedings of the years 2000 to 2016, aims to identify all available technologies and metrics for in-store-customer analytics. The search was based on the following keywords: Retail Analytics, Traffic Analytics, Operations Analytics, Behavior Analytics, Customer Analytics, In-Store Analytics, Video-Analytics, In-Store Metrics, Shoppers Intelligence, Path Analysis, Traffic Analysis and Costumer Counting. The databases searched were EbscoHost, IEEE Xplore, Springer Link and Google Scholar. As the Google Scholar results tended to overlap with the results of the other databases, the duplicates were eliminated. Furthermore, only journal publications and conference proceedings that were available via direct PDF download were selected. Overall, this search yielded a corpus of 284 papers.

By analyzing the titles and the abstracts of these 284 papers, 42 relevant papers were identified. These were studied in detail and led to the identification of 18 core papers that are the basis for this literature review (Table 3).

	EBSCOHost	IEEE Xplore	Springer Link	Google Scholar
Total results 284	48	96	28	112
After analyzing title and abstract: 42	12	14	7	9
After detailed analysis: 18	1	6	4	7

Table 2: Literature Selection

No.	Author	Technology	Alternative	Metrics Categories	Customer Identification	In-Store Metrics
1.	Sorensen (2003)	RFID	RTLS	Multiple Locations	Proxy Individualized	Density, Speed of Purchasing, Quadrants, Speed of Shopping
2.	Hong et al. (2004)	WIFI	-	Multiple Locations	Proxy Individualized	-
3.	Li-Qun Xu (2007)	Video-Analysis (CCTV)	Optical Sensors	Multiple Locations, Action Event	Individualized	Crowd Density, Customer Counting
4.	Senior et al. (2007)	Video-Analysis (CCTV)	Infrared-Beams, Pressure Pads	Multiple Locations, Action Event	Individualized, Identified	Customer-Counting
5.	Bolliger (2008)	GSM, Bluetooth, WIFI	-	Multiple Locations	Proxy Individualized, Identified	-
6.	Yada (2009)	RFID	-	Multiple Locations	Proxy Individualized	Shopping Time, Staying Time in Sales Areas,
7.	Bourimi et al. (2011)	GSM, Bluetooth, WIFI	RFID, Indoor GPS, CCTV, Photo Sensors	Multiple Location	Proxy Individualized, Identified	-
8.	Blecker et al. (2011)	RFID	CCTV,	Multiple Locations, Action Event	Proxy Individualized	Visited Product Zones, Contact Instances, Physical Movement of Goods
9.	Rai et al. (2011)	Video-Analysis (CCTV)	WiFi, RFID	Multiple Locations	Proxy Individualized	Shopping Time, Staying Time in Sales Areas,
10.	Takai et al. (2012)	RFID	-	Multiple Locations	Proxy Individualized	Shopping Time, Staying Time in Sales Areas,
11.	Cai (2014)	WIFI	-	Multiple Locations	Proxy Individualized, Identified	-
12.	Conell et al. (2013)	Video-Analysis (CCTV)	-	Multiple Locations, Interaction Event	Individualized	People Counting, Conversion Rate, Buying Time and Staying Time, Cart Localization, Basket Size, Line Counting
13.	Rallapalli et al. (2014)	Smart Glasses	CCTV, WiFi	Multiple Locations, Interaction Event	Proxy Identified	Shopping Behavior: Walking, Dwelling, Gazing, Reaching out
14.	Yaeli et al. (2014)	WIFI	GPS, RFID, WiFi, Bluetooth	Multiple Locations	Proxy Identified	Store Zone, Store Visit, Zone Transition, Zone Visit Time, Store Visit, Unique / Repeat Customer, Store Exit Time, Store Enter Time, Time per Zone, Visitors to Store,
15.	Zeng et al. (2015)	WIFI	-	Multiple Locations	Proxy Identified	Walking Fast / Slow, Staying Time
16.	Deva et al. (2015)	WIFI	-	Multiple Locations	Proxy Identified	Returning Visitors, Visit Frequency, Visited Zones, Buying and Staying Time
17.	Pierdicca et al. (2015)	Beacon Technology	-	Multiple Locations	Proxy Individualized	Total Number of People, Avg. Visiting Time, People Passing by, Avg. Group Number, Interactions
18.	Liciotti et al. (2015)	Video – Analysis (CCTV)	-	Multiple Locations, Interaction Event	Individualized	Visitors, Visitors of a Zone, Interaction with Shelf / with Person / with Products, Duration of Interactions, Avg. Interaction Time

Table 3: Literature Review

This search, which was deliberately conducted without bias for specific technologies yielded papers on data analysis technologies, most of which did either not mention stationary retail, or only mention it as an additional application option. This indicates that so far researchers have not really engaged with the topic of In-Store Customer Analytics. The analysis of the technologies discussed in the literature yields two main categories of data collection technologies. 1) direct measuring technologies, which are able to directly asses the customers and their actions and 2) proxy technologies, which assess the customers and their actions via a proxy (such as via their shopping trolley, their smartphone etc.).

The customer data collection of both categories (direct or proxy) can be measured in three different degrees. 1) non-individualized (customer cannot be traced and recognized as returning customer), 2) individualized (customer can be traced and recognized as returning customer) and 3) identified (customer can be traced, can be recognized as returning customer and can be identified specifically/ as named individual).

In addition to the question, how something is measured, the question what is measured can also be used for the classification, as a metrics category, for comparing the different technologies. The first type of technologies is designed to collect location metrics, which can either be done via a single location or via multiple location measuring points. While the single location data collection corresponds to an on/off signal, the data collected via multiple locations allows for more complex analyses (e.g., path analyses, heat maps etc). The second type of technologies measures more than just the physical movement of the customer (behavior metrics). The behavior metrics can be further divided into two subtypes. The first subtype consists of the measuring of 1) individual actions, (Actions) such as walking, waiting, looking at, touching, while the second subtype includes the measuring of 2) interactions, such as conversations with the shop assistants (interactions with staff) or the lifting up of products (interaction with products). In order to assess and interpret the performance of each of the metrics categories identified, a collection and classification of specific metrics must be created, which is described and discussed in Section 4.

3 Technologies for the Collection of Physical Customer Data

There are a myriad of technologies available to the retail sector for the collection of physical customer data. In our literature review, we identified eight different options, ranging from simple solutions such as infrared barriers to more complex systems, such as CCTV recording. In this paper, the merits of the different technologies are assessed independently. Potential cross-coordination of different customer data collection options and hybrid solutions will only be addressed in the outlook section of the conclusion. Table 4 below summarizes the performance range of each of these technologies with respect to the type of method (direct vs. proxy), the metrics categories that can be derived from these and the degree of customer identification. In the following section, the listed technologies will be assessed with regard to their advantages and disadvantages.

			Metrics category				
			Location metrics		Behavior metrics		
		Measurement	Single Location	Multiple Location	Action	Interaction	Customer identification
Sensors	Light Barriers	direct	yes	no	no	no	Not individualized
	Pressure pads	direct	yes	no	no	no	Not individualized
	Optical sensors	direct	yes	no	no	no	individualized
Proxy technologies	RFID	Proxy	yes	yes	yes	no	identified
	Beacon technologies	Proxy	yes	yes	yes	no	identified
	WIFI, GSM, Bluetooth	Proxy	yes	yes	yes	no	identified
	Smart Glasses	Proxy	yes	yes	yes	yes	identified
Tracking systems	CCTV	direct	yes	yes	yes	yes	identified

Table 4: Summary of In-Store Customer Analytics Technologies

3.1 Rudimentary Sensors

The use of pressure pads and light barriers for measuring customer data is the most rudimentary collection method for In-Store-Customer Analytics. Advantages; Low cost. Disadvantages: By means of sensing the interruption of a light beam, or by sensing a certain weight, these simple solutions yield a simple unreflected number, which can be quite inaccurate due to the simple mechanism that produced it. Groups of people, shop employees, suppliers or contractors, children playing near the door or animals wandering in all produce one hit. Thus these technologies are unable to perceive shoppers as individualized entities. For this reason, light barriers and pressure pads are a good tool for registering general trends in higher or lower shopper numbers, but do not yield a reliable number of the shop visitors [Se07].

3.2 Optical Sensors

The assortment of technologies that can be summarized under the heading ‘optical sensors’ ranges from motion sensors to infrared cameras. Advantages: The optical sensor technologies of the highest technical sophistication are able to follow visitors to a shop as individualized entities and to analyze their visitor behavior (path analysis, heat maps). As sensors are not able to identify visitors by name, there are no privacy issues. Disadvantages: Collecting data for groups of visitors tends to be a challenge for sensor systems and it should also be pointed out that these systems act independently of the customers and thus do not allow the customers the choice of opting out [Xu07].

3.3 Proxy Technologies

The group of proxy technologies includes collecting data via Wifi networks, RFID chips, the use of smart glasses, or using smartphones with indoor GPS tracking. The performance range of the individual technologies is very diverse [Bo09]. Advantages: Due to the fact that these technologies allow for individual customer identification, the advantages lie mainly in the cross-referencing with transaction data and other customer data, which makes it possible to individualize and customize the shopping experience by offering digital services responding to detected customer behavior. Disadvantages: It is important to remember that the customer behavior is not directly measured, but is extrapolated using proxies, which means that misidentifications and other misrepresentations of customer behavior can occur. This can lead to information gaps, e.g., if the customer leaves the context of the proxy, such as the RFID identified shopping trolley or does not carry a smartphone or has switched off the phone [So03] [Ca14] [Ya14].

3.4 Tracking Systems

CCTV systems are the most complex group of technologies for collecting in-store customer data. As their development was initiated by the surveillance industry [Xu07], these video systems are able to count customers, to follow and assess their shopping paths in store and to collect their actions and interactions. Advantages: They can analyze groups and distinguish relevant data from irrelevant data (e.g., human visitors from animals). Facial recognition software, as well as the interpretation of gestures and facial expressions allow for an immense data depth and density that comes very close to the quality of direct observation by members of staff [Li15]. Disadvantages: The use of CCTV recordings for customer data analysis has been criticized for privacy reasons [KPP12] [Co12].

4 In-Store Customer Analysis Metrics

In order to shift the focus from a technology-focused view of obtaining in-store customer data, we would now like to focus on the type of data that can be obtained, as this is of greater relevance for the shop owners, by creating a classification of in-store customer metrics and their relevance. Metrics can be subdivided into four building blocks 1) the core metric that provides the relevant data and is thus the central metric. The other parts are put as a prefix before the core metric, in order to further define it. These other parts are 2) the individualization prefix, which allows to infer behavior of identified customers 3) the numbering prefix, which defines the type of figure provided quantity, frequency, time interval to last registration, duration) and the use of the measured figure, which depends on the type of metrics (Count, Ratio or Count / Ratio), as well as 4) the relation prefix, which relates the measured metric to the overall values measured on a time basis (average per day / month / year (see table 5). A core metric will necessarily include a counting prefix, while individualization and relational prefixation is optional. In order to reduce the overall complexity, for the following analysis, we have not included all possible metrics variations, but have only looked at their core metrics. The core metrics thus represent other metrics that can be derived from them, depending on the type of metric. In order to assess possible derivative metrics, we have created a metrics toolbox

4*	3	2*	1
Relation prefix	**Numbering prefix (type of metrics)**	**Individualization prefix**	**Core metric**
Average / day Average / month Average / year	Number of (Count) Frequency of (Count /Ratio) Recency of (Count /Ratio) Time per (Ratio)	Unique New Returning Repeat	e.g. Visitor (Count)

Example Average (4) Number (3) of Unique (2) Visitors (1)

Table 5: Metrics-Toolbox | * = optional

The complete collection contains 20 core metrics identified in the literature review of the Web-Analytics Metrics, which represent a total of 1248 variations of in-store customer analysis metrics. Table 6 lists the core metrics identified and relates them to their metrics category, to the available technologies for collecting them and to the type of customer data they provide. In the next section, the maturity assessment matrix for customer data is introduced, which combines the different building blocks presented here and provides an overview of the different technologies and the core metrics they can supply.

Nr.	Core metric	Metric category	Single Location	Multiple Location	Action	Inter-action	Type of customer data
1.	Store Entry	Count	x				Non-individualised
2.	Store Exit	Count	x				Non-individualised
3.	Visitor	Count	x				Individualised
4.	Visited Zone	Count / Ratio	o	x			Non-individualised
5.	Visits	Count / Ratio	o	x			Individualised
6.	Group Visits	Count / Ratio	o	x			Individualised
7.	Visitors per Group	Count	o	x			Individualised
8.	Zone Visitors	Count	o	x			Individualised
9.	Zone Transitions	Count	o	x			Individualised
10.	Crowd Density	Count	o	x			Individualised
11.	Actions	Count / Ratio	o	o	x		Individualised
12.	Walking	Count / Ratio	o	o	x		Individualised
13.	Dwelling	Count / Ratio	o	o	x		Individualised
14.	Gazing	Count / Ratio	o	o	x		Individualised
15.	Reaching out	Count / Ratio	o	o	x		Individualised
16.	Interactions	Count / Ratio	o	o	o	x	Individualised
17.	Interactions with Products	Count / Ratio	o	o	o	x	Individualised
18.	Interactions with Staff	Count / Ratio	o	o	o	x	Individualised
19.	Interaction with Person	Count / Ratio	o	o	o	x	Individualised
20.	Interactions with Shelfs	Count / Ratio	o	o	o	x	Individualised

Table 6: In-Store Customer Analytics Core Metrics

Maturity Assessment Matrix for In-Store Customer Data

Stationary shop owners face a number of challenges. One of them is to compete with online retailers. So far, the advantages online retailers have due to their Web Analytics Data information and due to the fact that they can adapt their pricing and products accordingly has not been a major focus of the literature. The maturity assessment matrix introduced here provides an overview of the location and behavior metrics available (subdivided into single and multiple location, actions and interactions, ranging from simple location indication to complex analyses of customer behavior), allowing different levels of identification (non-individualized, individualized and identified) and assesses the performance of different data collection technologies. In addition, the maturity matrix also assesses the possible application range of the identified core metrics. The core metrics are entered into the matrix at their lowest possible range, and thus are also available at higher maturity, as parent directories are always available to lower branches of a family tree. Thus registering a ‘Visitor’ requires an individual one-location point measuring device as minimal requirement. But a more complex system, which can collect data from different locations and is able to identify customers specifically can still be used to collect the metrics ‘Visitor’. In the following diagram, proxy technologies are represented in dark gray font. A tick indicates that the technology has the relevant performance range. A zero indicates that this performance range is not available. White cells in the matrix indicate that the collection of behavior metrics (actions and interactions) is only possible if individualized or identified customer registration is available. Non-individualized data collection, such as via light barriers or pressure pads can only yield location metrics and are not able to register and identify physical actions (e.g., picking up a product) or interactions (e.g., talking to staff) .

If we focus on the information available rather than on the technologies used to collect data, it becomes clear that most of the core metrics identified here can be provided by systems that allow for individualized data collection. In addition, it becomes evident that specific customer identification is not a real advantage for mere customer data collection. This is different, though, if the aim is to cross-reference the data collected with customer databases.

Implications

In the digital world, customer data analytics is already firmly established. Stationary retailers can use customer data analysis for a range of development opportunities, such as gaining more information on customer behavior before they engage in a transaction. Retailers could use this information to tailor the available goods better to customer demand or to tailor the shop setup and product presentation better to the shopping paths of customers or to customer behavior or to review the impact of marketing activities on in-store customers. Furthermore, the data could also be used to plan staff availability, in terms of time and place of deployment [CM15]. Another relevant aspect experienced in the context of online retail is the fact that the mountains of data provided by Web Analytics have led to a constant assessment and readjustment of the offers and services provided.

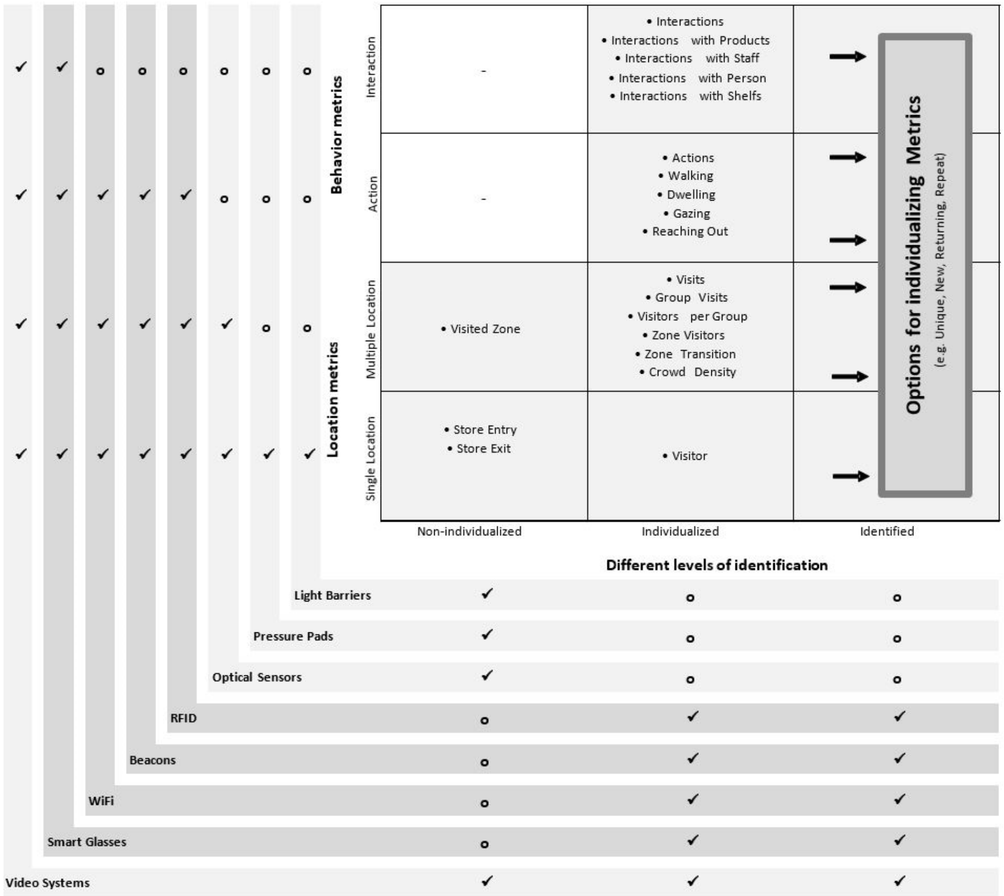

Figure 1: Maturity Assessment Matrix for In-Store Customer Data

And, while the most rudimentary data collection technology is error-prone and often yields imprecise data, even this rudimentary data collection offers a significant information insight. Thus even a simple light barrier would yield a trend-based conversion rate if cross-referenced with transaction data. However, groups of clients entering a shop is a challenge for most data collection technologies. And the fact that rudimentary technologies cannot clearly distinguish between customers and staff, between adults and children and between persons and animals must be taken into account. Nevertheless, retailers have the option to enter into the world of in-store customer analytics slowly, by using simpler technologies first and then upgrade to more complex options. The full range of customer data analytics is today only available using sophisticated CCTV recording systems. But for the majority of In-Store Customer Analysis Metrics, systems that allow for individualized customer registration are sufficient, systems such as optical sensor systems, which have the added advantage that they do not have privacy issues attached to them.

Conclusion and Recommendations

By means of our systematic literature review, the research questions formulated in the introduction can be answered in the following way: 1) Eight different technologies for the collection of in-store customer data were identified. Light barriers and pressure pads can be characterized as an imprecise solution, but are simple to use and easy to install. Optical sensor systems offer good insights, but do not allow for customer identification and thus cannot be used to customize the shopping experience. Proxy systems such as RFID, WiFi, beacon technology, smartphone registration and smart glasses provide a broad range of data collection options, but are characterized by data collection mistakes and data gaps, due to their indirect data collection system. Video-systems provide the widest performance range, but are also very complex and also have a number of challenges due to privacy issues. 2) 20 core in-store customer analysis core metrics were identified (see table 6), of which 1248 in-store customer Analysis metrics can be derived (see table 5). 3) By means of the maturity assessment matrix, the different aspects discussed in this paper were combined in order to provide an overview of the performance range of the different technologies and of the in-store customer metrics they can collect. This overview is intended to help retailers decide on what system they might implement, focusing on the type of information they can gain rather than focusing on the available technologies.

This is why this paper opted for a technology-independent overview of available data collection methods. Potential applications based on cross-referencing with transaction data as well as any hybrid systems (such as combining optical sensors with proxy systems) were deliberately excluded from the analysis. Hybrid solutions can overcome the data gaps of normal proxy technologies and also allow for the development of customized offers targeted at specific clients and still respect their privacy. Moreover, the cross-referencing of in-store customer data with transaction data and other customer data is a very interesting further research area for customer behavior in stationary retail. In-store customer analytics can be a basis for reorganizing your pricing, products and marketing setup in-store. In addition to improving your location-based services, it can also yield important information about customer behavior. [Fz15] Thus, stationary methods for customer data analytics are not only relevant in terms of catching-up to online retailers, but they also offer new business models that cannot easily be copied by online retailers. But in order to make this viable, the quality of the data collection needs to be improved and imprecise or incorrect data must be excluded by the system. It is also vital to work towards using hybrid solutions and work towards cross-referencing in-store customer data with in-store transaction data, but care must be taken not to infringe the customers privacy rights. Another important research area would be to add another type of metrics to the metrics classification, i.e., the metrics of context. The collection of context data requires an integrated cross-referencing of all available systems in order to find more context for customer behavior, by making use of behavior data and of historic data. Another important next research step would be to study the implementation and application of such systems in a practical setting, focusing on owner operated stationary retail outlets. The next logical research step would be to study the potential of cross-referencing transaction data with other customer data in an omni-channel retailing context.

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