COMPANIES' MATURITY FOR THE DEPRECATION OF THIRD-PARTY COOKIES

Lappeenranta-Lahti University of Technology LUT
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Timo Oksanen

Examiners: 1st Professor Anssi Tarkiainen
2nd Professor Liisa-Maija Sainio

ABSTRACT

Lappeenranta-Lahti University of Technology LUT
LUT School of Business and Management
Business Administration
Timo Oksanen

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Third-party cookies have played a major role in digital marketing as they enable companies to behaviorally target consumers. Due to the privacy issues related to third-party cookies, regulators have taken them under a magnifying glass and created regulations leading internet browsers to stop supporting third-party cookies. The purpose of this research is to develop a maturity model, that assists companies to prepare for the deprecation of third-party cookies.

The model developed has three dimensions: (1) First-party data, (2) Targeting, and (3) Develop marketing measurement. The model was tested on some of Dagmar's clients. The results implicate that the model serves its purpose well. The data from clients was collected via questionnaire and the answers were analyzed by using fuzzy logic.

The companies who answered received middle-range maturity levels. Almost all the companies weighted dimensions higher than the rating they gave to themselves. The best maturity levels were achieved in the First-party data dimension and the worst maturity levels in the Develop marketing measurement dimension.

TIIVISTELMÄ

Lappeenrannan-Lahden teknillinen yliopisto LUT
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Kauppatieteet
Timo Oksanen

Yritysten maturiteetti kolmannen osapuolen evästeiden poistumiseen

Kauppatieteiden pro gradu -tutkielma
2022
102 sivua, 10 kuvaa, 11 taulukkoa and 2 liitettä
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Keywords: Kolmannen osapuolen evästeet, Sumea logiikka, Maturiteetti, Digitaalinen markkinointi

Kolmannen osapuolen evästeet ovat olleet merkittävässä roolissa digitaalisessa markkinoinnissa. Kolmannen osapuolen evästeet ovat mahdollistaneet mainosten käyttäytymiseen pohjautuvan kohdentamisen. Niihin liittyvien yksityisyydensuojaongelmien takia internetselaimet enää tue niitä. Tässä tutkimuksessa kehitetyn maturiteetti-mallin tarkoitus on auttaa yrityksiä valmistautumaan kolmannen osapuolen evästeiden poistumiseen.

Kehitetyssä mallissa on kolme ulottuvuutta: (1) Ensimmäisen osapuolen data, (2) Kohdentaminen ja (3) Markkinoinnin mittaamisen kehittäminen. Mallia testattiin osalle Dagmarin asiakkaille. Tuloksista voidaan todeta, että malli suoriutuu tehtävästään hyvin ja tarkoituksenmukaisesti. Aineisto kerättiin kyselylomakkeella ja vastaukset analysoitiin käyttäen sumeaa logiikkaa.

Vastanneet yritykset asettuivat keskivaiheen maturiteetti-tasoille. Lähes kaikki yritykset antoivat ulottuvuuksille enemmän painoarvoa kuin, mitä antoivat itselleen arvosanaksi. Parhaimmat maturiteetti-tasot yritykset saivat Ensimmäisen osapuolen datasta ja huonoimmat Markkinoinnin mittaamisen kehittämisestä.

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I almost cannot believe that my moment of graduation is finally here. The journey from the beginning of my studies to this point was not easy and required countless hours of work and sleepless nights and it was like that from the beginning of my studies until the bittersweet end. Working full-time, playing competitive sports, and being active in student organizations while struggling to get all the study credits completed was the hardest challenge I have ever faced. Luckily I did not have to face these challenging years on my own. I want to thank my family and the close ones for making sure that I kept my studies on schedule and for enabling the difficult task of juggling between work, studies, competitive sports, and the positions of trust.

As the home stretch was getting closer and closer a final spurt was required to Finnish this thesis, which would not have been possible without the flexibility of my examiner Anssi and student counselors Kaija and Kirsti. I also want to thank Dagmar for giving me the opportunity to finish my degree with an interesting subject. I am highly grateful for the support I got from the Advanced Analytics and Martech team for writing this thesis. As an active student community member and a student advocate, I cannot even count the number of friends I have made throughout these years. I want to give my thank yous to all of you for making my time as a student unforgettable. Thank you Enklaavi, thank you LUT!

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Timo Oksanen

Contents

1 Introduction

The third-party cookie removal deviates from several other mega trends in the current world. Consumers arising concern of the data collected about them has ultimately led authorities to take actions. Globally 66 percent of adult consumers agree that tech companies have too much control over their personal data (YouGov 2021). In addition, 53 percent of internet users were more concerned about online privacy than a year ago than in 2019 (CIGI 2019). In 2018 European Union General Data Protection Regulation and in the United States somewhat similar legislation California Consumer Privacy Act went into effect. Both of which have the goal of protecting consumer's personal data.

Current digital marketing paradigm is highly dependent on third-party data. Third-party cookies allow marketers to behaviorally target consumers, which increases their willingness to pay for publishers to show their ads on websites (Ravichandran & Korula 2019). Companies are in need of assistance and instructions how to navigate in a world without third-party cookies. Maturity models are a practical way of translating difficult concepts into organizational capabilities and help raise awareness (Siew, Balatbat & Carmichael 2016). Maturity models help companies to reach the needs of market and as the deprecation of third-party is not just a passing trend but a disruption supported by current regulations, reaching the needs is not only for competitive advantage, but for survival in the industry. The goal of this master's thesis is to produce a maturity model to describe the progression of companies maturity for the deprecation of third-party cookies. The model is going to be used as a tool for getting a quick feedback on what level of maturity the company is. After the model is introduced it is presented to companies and the companies are classified based on their maturity results. Crises and sudden shifts in status quo often reveal what is broken, what is in need of healing and what matters (Gigliotti 2020). The maturity model developed in this thesis is meant to help companies to find these in the world without third-party cookies.

1.1 Motivation

Multiple major browsers have already removed the use of third-party cookies. According to Statista (2021) for example: Mozilla Firefox, Safari, Microsoft Edge have already removed them. However, Google Chrome has not done this yet, but privacy concerns have pushed Google to change how they track consumers (Sparkes 2022). In September 2021 Google Chrome dominated the global browser market with 65 percent market share over the Apple's Safari 18 percent (StatCounter 2021). In January Google announced that starting in 2022 Chrome would not accept Third-party marketing cookies (Statista 2021). However, in the summer of 2021 Google announced that they would take a step back in the process as the technology developed to substitute third-party cookies was not ready (Goel 2021). According to IAB (2022*b*) 22 Billion USDs is spent on third-party audience data and according to Statista (2020*b*) 4 Billion USDs is spent on identity solutions for marketing. Interestingly spending on third-party data continues to grow despite the challenges (IAB 2022*b*). In addition, 83 percent of marketers in the United States relied on third-party cookies in 2021 (MarketingCharts 2021). By interpreting only these measures one could argue that the deprecation of third-party cookies is a major disruption for advertisers and publishers.

A disruption like this has also enhanced other substitute technologies being developed, however some of them are in the twilight whether they are responsible or not as they have practically the exact same method to track users online as third-party cookies. Examples from these are Canonical name cloaking (CNAME) and fingerprinting as well as Google's own substitute solutions. Companies advertising online need to find alternative solutions. Currently there is a limited amount of research on how advertisers should tackle this disruption and if the industry is ready for it. This research contributes to the field of online marketing by providing a tool to assess companies' maturity for the depreciation of third-party cookies. Based on the classification of companies' maturity level we can interpret what are the capabilities companies are good at and what they need to develop.

1.2 Preliminary literature review

This subsection presents a preliminary literature review on two main aspects which add the motivation to this research. Literature on third-party cookies is very limited especially on third-party cookies deprecation. In addition, the current regulations as well as the European Commissions freshly approved acts on data are presented. However, some of them are so new that their actual effects and implementation are not clear yet.

1.2.1 Literature on third-party cookies

The academic literature on third-party cookies is quite limited and the ones that focus more on analysing the different capabilities of privacy concerned users and whether they choose to block third-party cookies or not (Englehardt, Reisman, Eubank, Zimmerman, Mayer, Narayanan & Felten 2015, Johnson, Shriver & Du 2020, De Corniere & De Nijs 2016). The studies also focus on the removal effects of third-party tracking (Beales & Eisenach 2014, Cofone 2017, Marotta, Abhishek & Acquisti 2019) and then there are more technical studies trying to define the third-party cookies and their usecases Cahn, Alfeld, Barford & Muthukrishnan (2016), Gomer, Rodrigues, Milic-Frayling & Schraefel (2013), Sanchez-Rola, Dell'Amico, Balzarotti, Vervier & Bilge (2021), Abraham, Athey, Babaioff & Grubb (2020), Demir, Theis, Urban & Pohlmann (2022), Cozza, Guarino, Isernia, Malandrino, Rapuano, Schiavone & Zaccagnino (2020). However, a more high ranking themes like privacy and targeting, however have more literature on them (Goldfarb & Tucker 2011, Liu, Sockin & Xiong 2021, Chen, Huang, Ouyang & Xiong 2021, Jai & King 2016). Third-party cookies have been the back-bone of web-tracking and digital marketing for a long time, however, there is a research gap on what are the options that companies need to take, when the third-party cookies are gone. Maturity models related to digital marketing and privacy have been presented by scholars (see: Boufim & Barka (2021)) as well as different consultancies, but they focus on privacy, B2B marketing and digital marketing in more upper level and usually the deprecation of third-party cookies is just mentioned. Furthermore, the research by IAB (2022*b*) shows a false sense of confidence: While the industry's sense of preparedness grows, actual implementation has made little progress. Furthermore, surveys regarding the demise of third-party cookies have been conducted, but only few of them focus on companies own assessment of their current state. And none of them have used fuzzy logic to address the impreciseness attached to the respondents own assessment. Additionally, most of the surveys and studies are conducted in the United States, where the privacy regulations are different than in the European Union.

Web tracking technologies are used to collect, store and connect user web browsing behavior. Based on this information advertising companies can accumulate it into user profiles and tailor more individualized ads for them (Schmucker 2011). These are further discussed later in the HTTP-cookies section. Tracking technologies also allow companies to do usability tests on their website and perform web analytics, which focuses more on e-commerce as whole rather than as a individual. Web analytics is used to maximise revenue, by evaluating the performance of each web page, what generated most traffic to the website and during which step of the order process a customer is lost (Schmucker 2011, Järvinen & Karjaluoto 2015).

Privacy concerns have become one of the most investigated attribute when it comes to web tracking(Kristol 2001, Sanchez-Rola, Dell'Amico, Balzarotti, Vervier & Bilge 2021). Privacy concerns and privacy in general has a major role in this current paradigm shift in web tracking, therefore it is important to define the privacy issues related to cookies before diving into more comprehensive definition of different cookies. Tracking devices like cookies have a range of benefits in user experience on the web. However, they can also make pieces of information public that people prefer to keep private, such as ethnicity, political opinions, sexual orientation or religion (Cofone 2017). Law enforcement and intelligence and intelligence agencies may use web tracking to technologies to spy on individuals (Schmucker 2011). To limit data sharing, consumers can utilize some type tracking prevention software which are available in the market. However, their effectiveness can be argued, because advertising networks are constantly finding ways to circumvent the actions for tracking prevention (Chen, Ilia, Polychronakis & Kapravelos 2021, Raschke & Küpper 2018). In addition the population of users that take actions to reduce data sharing is low and they tend to share a specific profile. However, they can still easily be targeted (Raschke & Küpper 2018, Johnson et al. 2020).

1.2.2 Regulations

Novel regulations like General Data Protocol Regulation (GDPR) in European Union and California Consumer Privacy Act (CCPA) in the United States have had major impact already in the tracking paradigm. In Canada the somewhat similar regulation to increase protection for user's personal information is Canada's Consumer Privacy Protection Act (CPPA) and in Brazil: Brazils General Data Protection Law (LGPD). However, there has been some research about the actual effects of these two regulations on both consumers and advertisers (Degeling, Utz, Lentzsch, Hosseini, Schaub & Holz 2018, Liu, Sockin & Xiong 2021). However, the two regulations differ from each other quite a bit even though they share the same goal. The most major difference in the web tracking context is the relationship to consent. In CCPA consent to share data is not required, but opting out must the possible. GDPR is more strict when it comes to consent to share data. GDPR requires opting in before any data sharing happens Johnson, Shriver & Du (2020). Based on the literature on this context it is quite controversial, that GDPR came in to act in 2018, still for example Degeling et al. (2018) argue that we lack functional mechanisms to give consent. This can be found concerning as the research by Englehardt, Reisman, Eubank, Zimmerman, Mayer, Narayanan & Felten (2015) found that an adversary can reconstruct most of a typical user's browser history, which makes browsers vulnerable for NSA's tracking no matter where their IP is located. To add insult to an injury older results from Gomer et al. (2013) show that there is a 99,5 percent chance that a user will become tracked by all top 10 trackers with 30 clicks on search results. In addition, most users might not even be aware, that they are a subject to tracking Raschke & Küpper (2018) and according to Cahn et al. (2016) 80 percent of the cookies harvested in their study were sent insecurely and with full permissions. The results presented by Englehardt et al. (2015) and Gomer et al. (2013) are good examples why systems like GDPR and CCPA, that increase the transparency of the web have value for consumers.

Something that is worth noticing in the data privacy context is that, even though GDPR came in to force in 2018 Degeling et al. (2018) found that the implementation of the new regulation has not been perfect. It has had positive effects on web transparency but still there are mechanisms that do not support opting in. A good example from this kind of mechanism is the new Google FLoC and its successor Google Topics, which were developed by Google to serve as a replacement for third-party cookies Block (2021). In addition, Liu et al. (2021) found that GDPR does not necessarily protect consumers as well as desired when it comes to social efficiency. The signs for privacy breaches, when it comes tracking, have already been noticed by for example Englehardt et al. (2015) and Beatrix Cleff (2007) even before GDPR required entities to take actions.

There has also been studies related to the consumer behaviour when it comes to data privacy questions.Chen, Huang, Ouyang & Xiong (2021) discovered that the privacy paradox is real. Surveys from data privacy indicate that most of us are concerned about our data and how it is used (MeasureProtocol 2020). However, according to Chen, Huang, Ouyang & Xiong (2021) there is no relationship between privacy concerned survey results and data sharing authorisations. Johnson et al. (2020) also found that the amount of opt outs is not in line with the results of surveys about privacy concerns. In addition, Johnson et al. (2020) found that consumers who opt out behavioral targeting share a few demographic factors. For example consumers who opt out tend to be more tech savvy, they are also older and live in wealthier cities. Research by Johnson et al. (2020) only focuses on opting out with the AdChoice program, which is not in line with GDPR so the results from their study cannot totally be interpreted in the EU. The effect that privacy concerns have on consumer behaviour also depends on the context. Goldfarb & Tucker (2011) have found that if ad is both obtrusive and well targeted, the ad does not perform well. This interaction with high contextual targeted ads and high visibility can be explained with privacy concerns of the consumers and the privacy related to the product category. This finding is something advertisers could take into account when they are planning their banner ads when the behavioral targeting is not available.

In addition, European Commission has approved in the early 2022 Digital Services Act (DSA) and Digital Markets Act (DMA) (EuropeanComission 2022*a*,*b*,*c*). They have two main goals:

1. to create a safer digital space in which the fundamental rights of all users of digital services are protected;
2. to establish a level playing field to foster innovation, growth, and competitiveness, both in the European Single Market and globally.

From marketers point of view the agreed DSA text include obligations to consent and access to services, that will take away the right of publishers to independently hold a dialogue with the user, asking them for a consent in case a software privacy setting is set. In addition, the text includes a ban on targeted advertising to minors and use of special categories of personal data IAB (2022*a*). The DMA should put an end to the ever-increasing dominance of Big Tech companies, as they must show that they allow fair competition on the internet. DMA establishes a set of narrowly defined objective criteria for qualifying a large online platform as a so-called "gatekeeper". These gatekeepers then need comply with certain set of rules and if they do not , they are punished. In a nutshell, they are not allowed to use unfair practices towards the business users and customers that depend on them to gain an undue advantage (EuropeanComission 2022*b*). With the DMA, Europe is setting standards for how the digital economy of the future will function. However, it will be up to European Commission when the new rules are implemented (EuropeanComission 2022*a*). From marketing perspective the true effects DMA is going to have are still to be decided (IAB 2022*a*).

1.3 Goal and limitations

The purpose of this research is to describe the removal effects of third-party cookies in the current digital marketing paradigm, valuate the maturity of companies for the paradigm shift and investigate what capabilities have greatest effect on companies perception of their own maturity. The goal of the research is to develop an easily adoptable self-assessment tool for companies to map their level of maturity and give them insights what they need to develop to ascend to the next maturity level. The goal is not to build a another general digital marketing maturity model as plenty of them already exist.

This research maps the removal effects of third-party cookies and the complimentary methods from the existing literature to define the capabilities for the maturity model. In addition, the existing maturity and readiness frameworks are studied. In the empirical section the developed maturity model is used to evaluate companies maturity with fuzzy methods. Based on the results the companies are classified to maturity levels.

The main research questions set for this research are:

1. How to evaluate companies' readiness and maturity for the deprecation of third-party cookies
2. What is maturity level of companies for the deprecation of third-party cookies

In the theory section the concepts of third-party cookies and maturity models are presented for the reader to have clear unified interpretation of the entirety. To achieve this common conception the following sub-questions are presented:

1. What are HTTP cookies
2. Why third-party cookies are being removed
3. What are the options for companies after third-party cookies are gone

In this research the focus is only on the third-party cookies. However, during the beginning of 2022 there has been arguments about the legal compatibility of large enterprises data operations in Europe under GDPR. Currently the discussion is mostly pointed to Google Analytics. However, privacy concerns also strike social media and other major companies with large data sets from their users.

Sanchez-Rola, Dell'Amico, Balzarotti, Vervier & Bilge (2021) argue that cookie tracking in third-party context is just the tip of the iceberg. However, to maintain the scale of this paper suitable for master' theses the scope is only going to be in the third-party cookies, even though the third-party cookies are highly related to the whole paradigm shift in session-based web analytics and social media tracking, which first-party tracking in a third-party context. In addition the maturity model presented in this thesis does not give companies a guide on how to implement the steps to maintain a maturity level or ascending to the next level. The maturity model developed does not measure digital marketing maturity per se, but focuses specifically on the third-party cookies.

1.4 Research execution

The strategy of this research is to collect data via questionnaire developed in this thesis. The goal of this research is to develop a marketing maturity model to specifically measure quick and effectively the maturity level of companies for the deprecation of third-party cookies. The purpose of this research is first to describe the functionalities of third-party cookies and the removal effects that have already taken place in the marketing ecosystem as well as diving into to complimentary mechanisms emerged. In addition, we will study the current regulations which initialized the deprecation of third-party cookies.

Nature of this research is quantitative as we try to quantify companies' answers to questionnaire with fuzzy logic in order to capture their maturity rating. As this research is done a thesis for business studies majoring in marketing a certain level of societal sciences needs to be included. Hence, in addition to developing a tool to measure maturity, the companies who have answered the questionnaire are going to be classified into groups based on their maturity level. In the theoretical section the theoretical frameworks used in this research are presented, based on which the empirical evidence is collected. In the empirical section the material is collected with the aforementioned survey after which the results are analysed and presented.

1.5 Report structure

The research report consists of seven chapters (figure 1). First chapter acts as a introduction for the research with the inputs being the background of the research and the subject. The chapter presents the research's purpose, goals, research questions, limitations and execution methods. The second chapter presents the answers to sub-questions of the research from literature by defining the HTTP cookies and the complimentary mechanisms for third-party cookies in order to give the reader clarification for the central definitions and concepts about the subject of the research.

Chapters three and four focus on the first research question: *How to evaluate the* *companies' readiness and maturity for the deprecation of third-party cookies* as the chapters consists of presentation of different maturity models based on which the used maturity model and the questionnaire to measure the model is developed. Chapters three and four are presenting the theoretical frameworks which are used as the input for the collection of empirical material. Fifth chapter presents the methods for the material collection for the empirical analysis to answer the second research question: *What is maturity level of companies for the deprecation of third-party cookies.* This includes presenting the questionnaire used and the defining the fuzzy logic approach used to analyse the answers.

The research questions, goals and the central results act as the inputs of chapter six. In chapter six the results of the answers are presented alongside with the analysis on the material collected. Chapter six also includes answer to the research questions, conclusions, and recommendations for further research. Chapter seven is the summary of the research, where the research's goals, execution, central results and conclusions are reviewed.

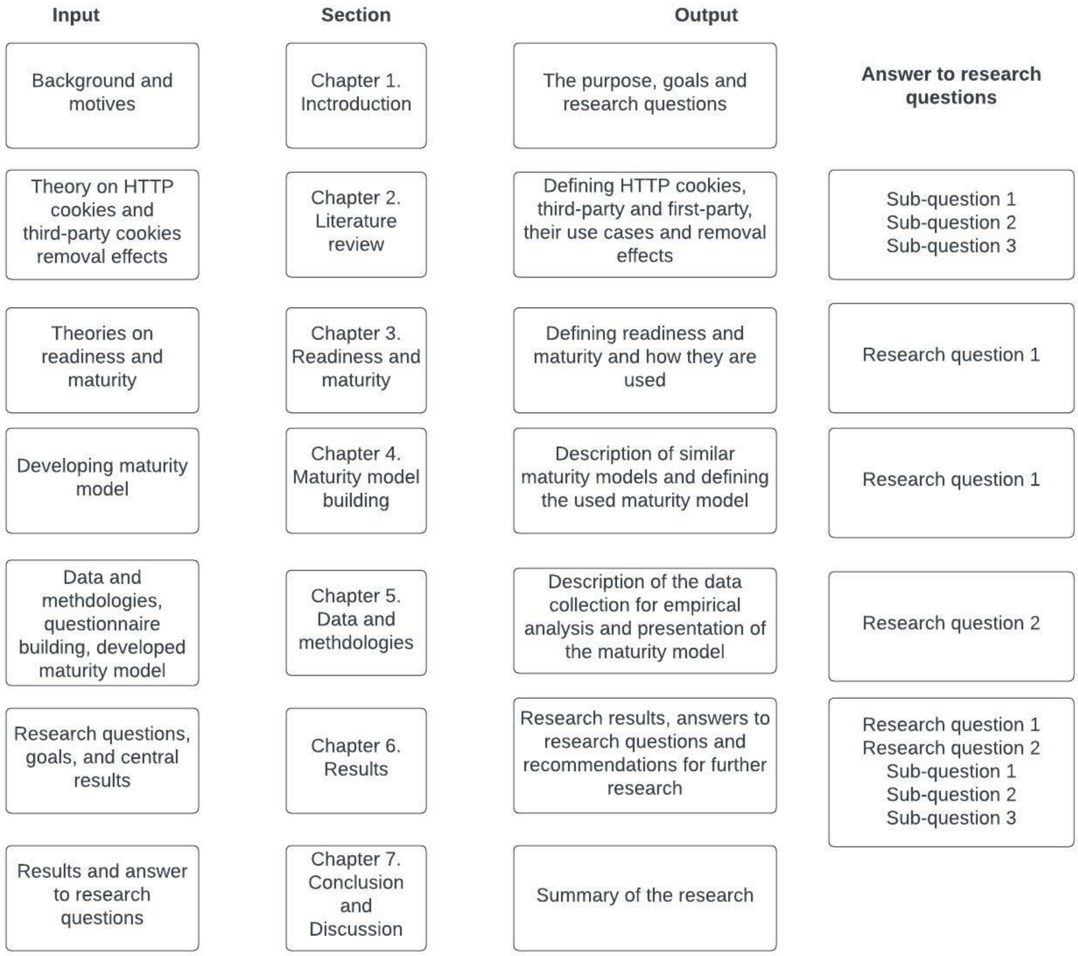

Figure 1: Report structure as input-output -chart

2 Literature review

In this chapter we are going to define HTTP-cookies and present the theory behind maturity models and readiness.

2.1 HTTP-Cookies

Services like Facebook, Google and other would not be free without advertising (Raschke & Küpper 2018) Cookies have been in a vital role in the current web advertising paradigm. They are comprehensively used around both publishers and advertisers.

Even user experience requires the use of cookies. (Cahn, Alfeld, Barford & Muthukrishnan 2016) Cookies can be distinguished from each other based on the way how they are created and used(Chen, Ilia, Polychronakis & Kapravelos 2021). In this chapter we are going to define cookies based on existing literature as well as review the privacy paradigm in the web.

2.1.1 First-party cookies

HTTP cookies in general are a small snippet of code stored into user's browser (Schmucker 2011, Mayer & Mitchell 2012, Cahn et al. 2016, Kristol 2001, Cofone 2017). Cookies can be distinguished into two categories based on their expiration period: *persistent* and *session*. A *persistent* cookie can keep the data in browser until a date specified by the *expires* attribute. *Session* cookie can keep data without these attributes, and is deleted when the session end (Takata, Ito, Kumagai & Kamizono 2021).

Cookies are commonly used for session handling, storage of site preferences, authentication and the identification of clients Schmucker (2011), Takata et al. (2021). The cookies that are set when visiting a website are considered as first-party, while those set by other domains as a result of loading external resources are considered as third-party. Consequently, if the same third-party resource is present on multiple websites, it enables cross-site tracking: any third-party domain that host resources referenced by multiple websites can track users across these sites (Chen, Ilia, Polychronakis & Kapravelos 2021). In other words, cookies allow websites to identify the device when it visits the website again, remembering some information about the previous interaction (Cofone 2017).

HTTP cookies in general make navigation faster, obviate the need to enter information such as language preference or username and passwords repeatedly (Cofone 2017). First-party cookie monitoring is mostly used to improve the services on the website and enable technologies like shopping cart (Demir et al. 2022). While third-party cookies are vanishing, First-party cookies and first-party tracking as well as social media tracking are not going anywhere.

2.1.2 Third-party cookies

In the early days of the web, content was designed and hosted by a single person, group, or organization (Mayer & Mitchell 2012). Third-party cookies are widely used technique in the web Schmucker (2011), Mayer & Mitchell (2012), Cahn et al. (2016). According to Sanchez-Rola, Ugarte-Pedrero, Santos & Bringas (2017) third-party cookie-based tracking is the most common form of tracking. Almost everything we do on web is tracked (Schmucker 2011, Sanchez-Rola et al. 2017). Web-tracking can be categorized multiple ways, one way is to categorize them in to stateless or stateful, depending on whether or not they require data to be stored in user's computer to properly function (Sanchez-Rola et al. 2017).

Third-party web tracking refers to the practice by which an entity (the tracker), other than the website directly visited by the user, identify and collect information about web users (Dao, Mazel & Fukuda 2021). This is why third-party cookies are the thing that allows marketers to do behavioral targeting (Schmucker 2011, Cahn et al. 2016, Demir et al. 2022). Third-party cookies are not set for the domain the user is currently viewing, but for external domains from which additional data, such as images and scripts, were fetched. Third-party cookies are sent to the corresponding server no matter which page the user is currently viewing, as long as it includes content from said third-party (Schmucker 2011).

Behavioral targeting is a form of targeted advertising, which tries to guess appropriate ad content based on collected user profile (Schmucker 2011). These cookies are often called tracking cookies, which collect demographic information about the user, such as age, gender, product preferences, and the most important information for marketers: the previous searches (Cahn et al. 2016, Englehardt et al. 2015). Generally, the use of third-party cookies has been rationalized since consumers do not want to see advertisements in the web that they do not find interesting. Behavioral advertising allows advertisers to use their marketing budget more efficiently by only targeting customers who are most likely to become customers. Studies have shown that behavioral targeting significantly increases the effectiveness of online advertisement (Schmucker 2011). However, behavioral targeting also carries a risk for a consumer. For example Liu et al. (2021) found that behavioral targeting can feed the addiction consumers have on temptation goods. The claim to utilize behavioral targeting to show consumers more targeted ads can also have a monetary backslash (Goldfarb & Tucker 2011).

From more technical point of view presented by Sanchez-Rola et al. (2021) the cookie ecosystem has myriad intermediaries, when from the more advertising-based point of view there are just few to several actors in the ecosystem: advertiser, auction and publisher (Gomer et al. 2013). A more simple process of third-party cookie ecosystem is presented in the figure 1:

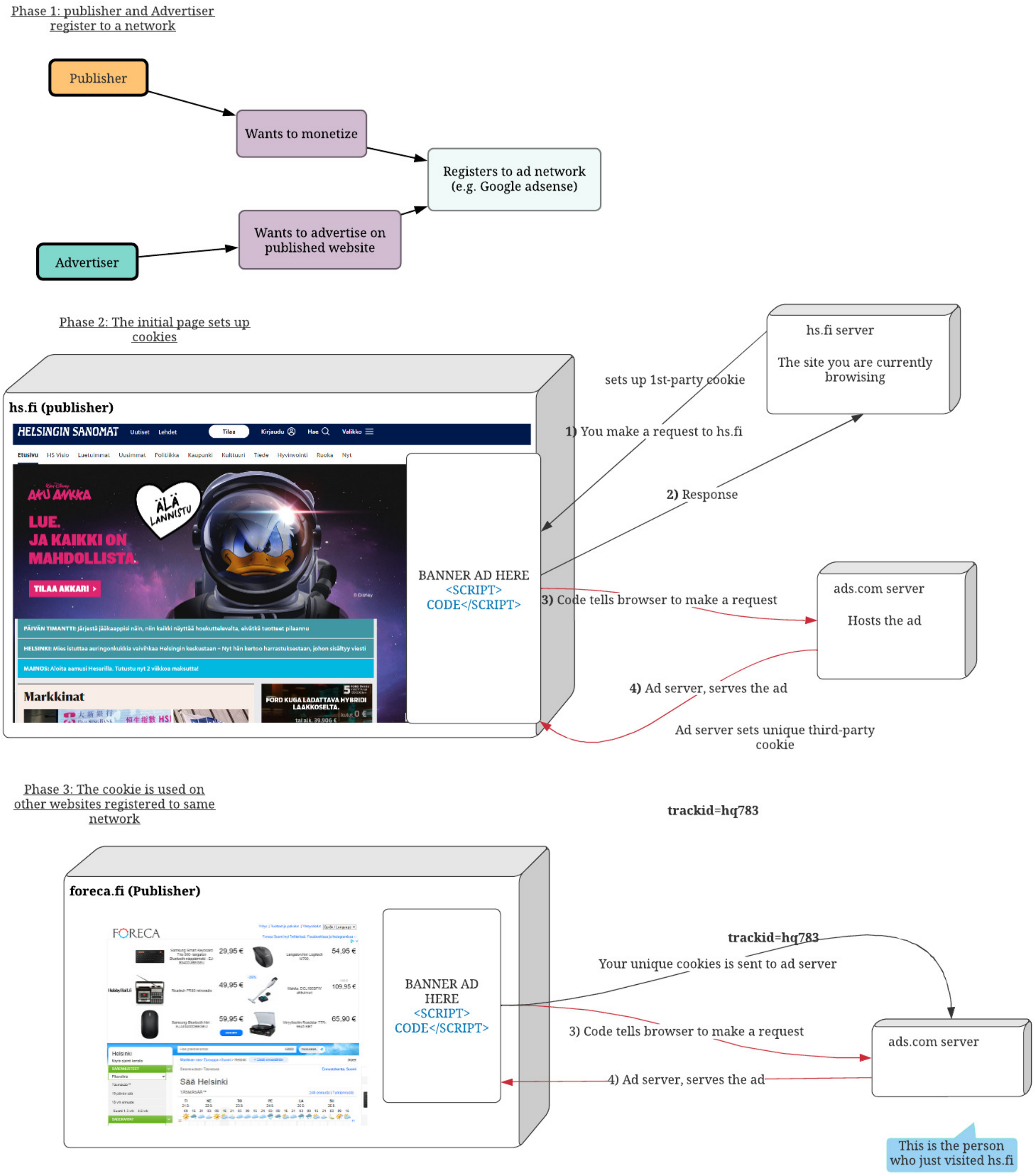

Figure 2: Simplified process of how third-party cookies are set

A good example how a consumer can cross paths with Third-party cookies is when they are browsing flights for a vacation and the following day, they start to receive advertisements related to the target country or city of the vacation they were browsing. From more technical point of view, the third-party cookies are set when a first-party page embeds third-party content (Mayer & Mitchell 2012).

2.2 Removal effects of third-party cookies and behavioral targeting

Advertising network has had their incentives to utilize third-party tracking even with the aforementioned disadvantages related to them. For example Cofone (2017) argues that the click-through-rate of advertisements increase approximately 670 percent with online behavioural advertising compared to traditional advertising. This kind of increased value creation increases advertisers willingness to pay the premium attached to behavioral targeting.

The depreciation of third-party cookies is already affecting the paradigm of measuring digital marketing. For example, Markov's Chain based attribution modeling is not going to be possible when third-party cookies are no more available (IAB 2022*b*). Consumers can see this phenomenon by the increasing number of contents behind the payment wall or registration. Decreasing of the complimentary content is a result from the monetary effects the depreciation of third-party cookies has in the whole digital advertising ecosystem(Ravichandran & Korula 2019, Marotta, Abhishek & Acquisti 2019, Beales & Eisenach 2014, Johnson, Shriver & Du 2020).

Degeling et al. (2018), Chen, Huang, Ouyang & Xiong (2021), Cahn et al. (2016), Gomer et al. (2013), Johnson et al. (2020) have all shown that the use of cookies can have negative effects alongside with functionalities that they provide. Still it is only when the disabling of third-party cookies is coming into a reality. There are some studies about the monetary effects of third-party cookies and behavioral targeting for example Ravichandran & Korula (2019), Johnson et al. (2020), Beales & Eisenach (2014), Marotta et al. (2019).

The results of the studies regarding the monetary effects of behavioral targeting have been somewhat different from one another. For example Ravichandran & Korula (2019) found that disabling third-party cookies has a declining effect on publisher revenue and majority of top 500 publishers have losses 50 percent or more. Johnson et al. (2020) found publishers receive 52 percent less revenue from users who have opted out of online behaviour advertising. Though this loss represents only 0,16 percent of total exchange revenue because opt-out impressions are so rare. In addition, Beales & Eisenach (2014) found that users without cookies Users without cookies generate at least 37,5 percent (when compared to users with new cookies) and up to 66 percent less revenue (compared to users with longer-lived cookies). The more long tail the publisher is the more are dependent on 3rd party cookies. One could make an argument here that the companies that suffer the most from third-party cookie deprecation are the small companies. On the other hand Marotta et al. (2019) found that When third-party cookies are available for publishers, their revenue only increases only about 4 percent. So the allocation of the premium paid by the merchants (those who want that their ads are shown) is unclear. Based on this research it would not make sense that publishers would not lose that much money to make radical changes on the free content. However, as mentioned before publishers still do have increased the amount on content behind an payment wall. The results of academic research are in line with the survey results from IAB (2022*b*) as the buy side cost per million impressions is increasing.

2.3 Complimentary mechanisms for third-party tracking

First-party cookies however, can be exploited to be utilized similarly as third-party cookies and still carry the privacy risks. For example Chen, Ilia, Polychronakis & Kapravelos (2021) found that 97,72 percent of the websites have first-party cookies that are set by third-party JavaScript, and that on the 57,66 percent of these websites there is at least one such cookie that contains a unique user identifier that is diffused to multiple third parties. Even when users have blocked third-party cookies, first party cookies can still be used to track consumers. Sanchez-Rola et al. (2021) discuss that the cookie journey is actually more complicated than what we have anticipated from before. Sanchez-Rola et al. (2021) also introduced a new definition of cookie ghostwriting, which relates to cookies that are set for a party (e.g. the website the user is visiting at the moment), but are actually created by a different entity (e.g. script loaded from a advertiser). According to Sanchez-Rola et al. (2021) creating a first party cookie from external library would not pose privacy problems per se, but in the study they found out that ghostwriters often send themselves a copy of the first-party cookies they have created, making it possible for them to track even users who have only accepted first-party cookies.

Alongside with cookie ghostwriting, another techniques to track consumers without third-party cookies have emerged even before Google announced that third-party cookies would not be supported in Chrome browser. One of them is fingerprinting and the another one is called DNS CNAME cloaking.

2.3.1 Fingerprinting

Web browsers share device-specific information with servers to improve online user experience, which allows companies to fingerprint users (Gómez-Boix, Laperdrix & Baudry 2018, Boda, Földes, Gulyás & Imre 2011). Fingerprinting can be exploited by companies in a similar fashion to cookie- and IP-address-based tracking. It does not leave persistent evidence behind on the client computer (Schmucker 2011). As the nature of browser fingerprinting is stateless it is harder to detect and even harder to opt-out (Upathilake et al. 2015). Deleting cookies does not protect against fingerprinting techniques(Raschke & Küpper 2018). According to study by Upathilake, Li & Matrawy (2015) there are three distinct categories of fingerprinting techniques: Web browser fingerprinting, website fingerprinting and signal fingerprinting. Web browser fingerprinting techniques can be grouped into: browser specific fingerprinting, JavaScript Engine fingerprinting and Cross-browser fingerprinting.

In browser fingerprinting wide range of data about the device is collected through browser Application programming interfaces (APIs). Modern devices enable that fingerprints collected like this exploited to track users (Gómez-Boix, Laperdrix & Baudry 2018, Laperdrix, Bielova, Baudry & Avoine 2020). Iqbal, Englehardt & Shafiq (2021) found out that 10 percent of the top 100 000 websites use browser fingerprinting and 25 percent of the top 10 000 websites. In canvas fingerprinting users are tracked with HTML5 canvas element to identify variances in users' Graphing processing unit (GPU), graphic drivers and graphic cards (Upathilake et al. 2015, Raschke & Küpper 2018, Acar et al. 2014). JavaScript engine fingerprinting uses browsers underlying JavaScript Engine for browser identification (Mulazzani, Reschl, Huber, Leithner, Schrittwieser, Weippl & Wien 2013). To utilize cross-browser fingerprinting, website operator needs to choose some browser-independent features as a basis of identification (Boda et al. 2011). Cross-browser fingerprinting differs from browser specific fingerprinting as it uses browser-independent features to generate the fingerprint (Upathilake et al. 2015).

Similar like web cookies, fingerprinting has both constructive and destructive uses. Using websites fingerprinting to ensure that the users trying to access their services actually are who they claim to be. Using fingerprinting to track users and display customized ads based on browsing habits can be considered as destructive use. In addition, fingerprinting can be used to deliver malware (Upathilake et al. 2015). Most importantly, the user has no control over the fingerprinting collection process since the tracking scripts are silent and executed in the background (Laperdrix et al. 2020). It is usually considered that stateless tracking methods like fingerprinting are harder to limit and block because they easily bypass common countermeasures against tracking such as private browsing or removing cookies (Sanchez-Rola et al. 2017).

Related to fingerprinting, other mechanisms to track users are evercookies and cookie syncing. Evercookie is a resilient tracking mechanism that utilizes multiple storage vectors. In other words, when user visits a site that uses evercookies, the site issues an ID and stores it in multiple storage mechanisms. If the user removes his HTTP cookies the ID stored before can be used to create the same cookies again. Cookie syncing is the practice of tracker domains passing pseudonymous IDs associated with a given user. (Upathilake et al. 2015, Acar et al. 2014)

2.3.2 DNS CNAME Cloaking

Domain Name System's (DNS) most important responsibility is to resolve human-readable domain names to numeric IP addresses (Aliyeva & Egele 2021, Dao, Mazel & Fukuda 2021). The DNS is organized as a distributed database, and its data entries, also known as Resource Records. They are commonly defines by three attributes: type, name, and value (Aliyeva & Egele 2021). In other words DNS can be seen as the phone book which has all the corresponding phone numbers of names. One of the Resource Records is called Canonical name (CNAME). CNAME records introduce aliases into the DNS system and use domain names for both its name and value attributes (Aliyeva

& Egele 2021). To put it more simply CNAME is used to map domain name to another. This mapping is commonly used to host multiple services on the same IP. To do so, one creates an alias (CNAME) for each service that all refer to same DNS *A* record of *example.com*. However, the CNAME can also point to another server. When the CNAME of *example.com* points to *otherwebsite.com* it means that the browser will load the content from *otherwebsite.com* and not *example.com*. This technique is known as CNAME Cloaking (Demir et al. 2022, Dao & Fukuda 2020).

Domain Name System (DNS) CNAME records with the use of Content Delivery Network (CDN) is used to improve website load times and increase the overall performance of the site, however CNAME is also used for targeting (Ren, Wittman, Carli & Davidson 2021, Dao, Mazel & Fukuda 2021). The use of CNAME records for targeting is misusing of the technology, against browser policies and generally holds risk for major privacy issues (Ren, Wittman, Carli & Davidson 2021, Aliyeva & Egele 2021, Takata, Ito, Kumagai & Kamizono 2021, Dimova, Acar, Olejnik, Joosen & Goethem 2021). CNAME Cloaking is another example of techniques developed in the race against third-party tracking blocking methods and consumer privacy concerns (Dao et al. 2021). Similar technique to evade regulations and limitations to share cookies is called Link Decoration. In link decoration a first-party cookie is embedded in third-party URLs and shared. Link decoration is often used for third-party content in first-party websites (Takata et al. 2021).

Simply put; CNAME cloaking disguises the requests for third-party tracking as first-party tracking (Dao et al. 2021). A basic example here would be that a user accesses the website *example.com* which has embedded a first-party tracker in it's subdomain *a.example.com*, which points to a tracking provider *ad.com* via the CNAME *m.ad.com* and the tracking provider *ad.com* can track the user (Dao et al. 2021, Dao & Fukuda 2020). Because the tracking is inside the same DNS hierarchy, where *example.com* is the main domain and *a.example* is the subdomain the tracking blocking approaches cannot identify and blacklist as a third-party tracker. However, Dao et al. (2021), Dao & Fukuda (2020) found out that some blocking extensions work quite well but most of them are not able to block CNAME cloaking-based tracking effectively. In addition, as the problem arising from CNAME cloaking is not well studied, the overall mitigation against it are nascent even though there are several regulations implemented to related to third-party cookies (Ren et al. 2021, Demir et al. 2022, Takata et al. 2021). Most concerning privacy risks are that websites that hold sensitive information have been using CNAME Cloaking and even the strictly necessary cookies on first-party websites have been shared with CNAME cloaking (Dao et al. 2021, Takata et al. 2021).

According to Dimova et al. (2021) CNAME-based tracking may hold additional security risks compared to other third-party trackers because CNAME-based trackers are included in the *SameSite* context. *SameSite* is one of the attributes attached to a cookie and it can prevent cross-site request forgery attacks (Takata et al. 2021). Other browser extensions can protect cookies but CNAME cloaking and link decoration can bypass the *SameSite* attribute (Takata et al. 2021, Dimova et al. 2021). Some of the existing approaches to detect third-party tracking use blacklisting approaches, some approaches identify tracking requests using cookies or fingerprinting. Dao & Fukuda (2020) have suggested an approach based on machine learning on how to detect CNAME Cloaking, which outperformed well-known tracking filter. However, in CNAME cloaking a CNAME record in Domain Name System (DNS) is used to hide usual tracking domains that are blocked by browser filter lists and extensions and this is how CNAME cloaking behaves differently from ordinary third-party tracking because it uses first-party subdomains which are not impacted by browsers and extensions(Dao & Fukuda 2020, Dao et al. 2021).

According to study by Dao et al. (2021) the usage of CNAME Cloaking based tracking has increased significantly from 2016 to 2020 and in January 2020 0,59 percent of Alexa top 300 000 websites included CNAME Cloaking tracking. Similarly Ren et al. (2021) found out that non-negligible fraction of the Alexa-10 000 websites perform CNAME cloaking-based redirections, all though some of these re directions can be unintentional. Demir et al. (2022) found out that the 76 percent of the 15 000 top sites analyzed utilized CNAME cloaking-based tracking and over the year 2021 such tracking cookies have increased by 50 percent. Dimova et al. (2021) found out in their study that 95 percent of websites studied by, that included at least one CNAME-based tracker, leak more than one cookie.

It is worth noticing that even though methods like CNAME cloaking, link decoration and fingerprinting do not use third-party cookies per se, but the methods are somewhat the same as third-party cookies; users' personal identifiers are used for tracking purposes. This is why these techniques and methods are not an option if the company wants to act responsibly and be in line with the current privacy regulations.

2.3.3 Social media tracking

According to Schmucker (2011) the most simple social media tracking example is the Facebook Like-button. can be seen as a web bug. It is typically included as an inline frame (iframe), that is, an own HTML page nested inside the current web site. When this inline page is requested, the address of the main page, along with Facebook's session cookie, is sent to the Facebook servers. This allows Facebook to see which other pages their customers are browsing. Social media data is then used to enrich customer data (Schmucker 2011). In other words, one could argue that social media platforms do third-party tracking in a first-party context. The process of social media tracking is presented in the figure below:

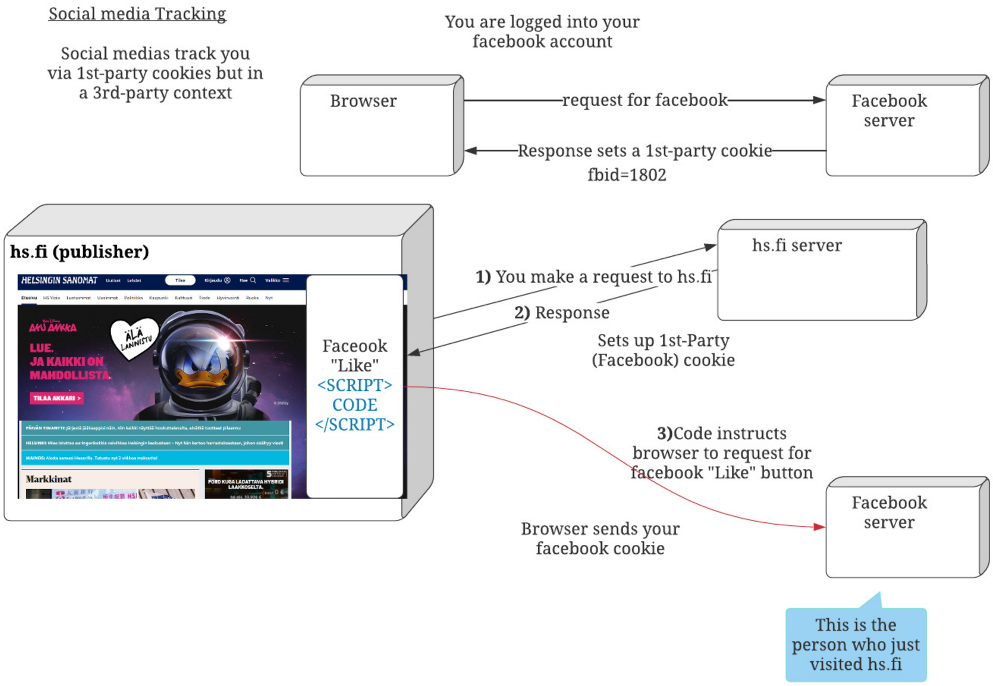

Figure 3: Simplified process of how social media tracking works

2.3.4 Contextual advertising

Contextual advertising refers to presentation of ads that are related to the content of the website (Schmucker 2011, Zhang & Katona 2012, Fan & Chang 2010, Li, Wang, Zhang, Cui, Mao & Jin 2010, Broder, Fontoura, Josifovski & Riedel 2007, Anagnostopoulos, Broder, Gabrilovich, Josifovski & Riedel 2007). This can be done via keywords representing the overall topic of the page. Contextual advertising is based on the contents of the website alone so it does not depend on tracking techniques (Zhang & Katona 2012, Schmucker 2011). In other words, a content like blog post becomes a platform for expressing personal opinion (Fan & Chang 2010). As behavioral targeting in its current format is coming to an end one could argue that this would be a renaissance for contextual advertising. Contextual advertising ecosystem has similarities with the third-party cookie ecosystem, but in contextual advertising the most prevalent pricing methods are based on clicks or impressions (Li et al. 2010, Broder et al. 2007).

One of the problems related to contextual advertising lies in the fact that web page content can change overtime. When page content is static, the ad server can invest computation resources in a one-time offline process that involves analysing the page content and the ad can be matched with the content of the page. However, dynamic pages which cannot be processed beforehand require significantly more prohibitive communication and latency costs. If the page content cannot be analyzed in advance it will lead to low-relevance ads, which means fewer clicks or impressions, higher communication and preprosessing load, and to high latency. This leads to poor user experience and the user even might be gone before the ad arrives. (Anagnostopoulos et al. 2007)

3 Change readiness and maturity

The demise of third-party cookies is a disruptive change so assessing readiness and maturity for disruption and change is topical. Readiness in ordinary language connotes a state of being both physically and behaviorally prepared to take action (Weiner 2009). Change readiness is often related to topics like change management and innovations, as well as creative destruction (Bergek, Berggren, Magnusson & Hobday 2013). Technological discontinuities like the demise of third-party cookies drive creative destruction. Already, new complimentary technologies have emerged and some have become obsolete in the rapidly changing marketing technology industry. Change is inevitable and companies need to be prepared for the change and innovation capabilities to answer the change have gained increasing interest(Lee, Chang & Chien 2011, Gill & VanBoskirk 2016). Scholars have created several frameworks to measure and model companies preparedness, readiness and maturity for change.

A theory of organization readiness for change

Organizational readiness for a change is multi-level construct. Readiness can be more or less present at individual, group, unit department, or organization level. Readiness can be theorized and assessed, and studied at any of these levels of analysis. As an organization-level construct, readiness for change refers to organizational members' shared resolve to implement a change (change commitment) and shared belief in their collective capability to do so (change efficacy). Specifically, organizational readiness refers to organizational members' change commitment and change efficacy to implement organizational change.(Weiner 2009) The determinants and outcomes of Organizational readiness for Change are presented in the figure below:

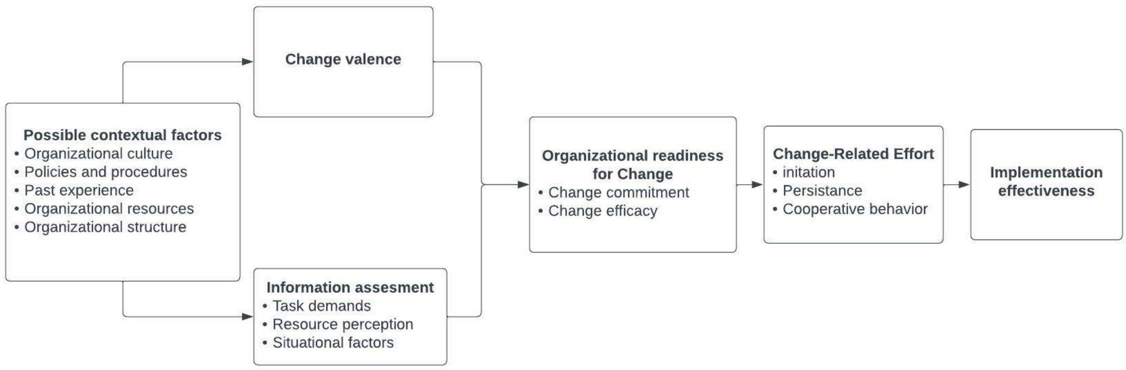

Figure 4: Determinants and Outcomes of Organizational Readiness for Change (Weiner 2009)

The determinants of Organizational readiness for change are possible contextual factors, informational assessment and change valence. Contextual factors are related to the culture, procedures, past experiences, resources and structure. Organizational readiness for change is a function of change valence, which in this context means the level how much organizational members value the change, and how favorably they appraise task demand, resources and situational factors. (Weiner 2009)

Multilevel Framework of change readiness

Rafferty, Jimmieson & Armenakis (2013) have developed another multilevel framework of change readiness. In their framework presented in the figure. They specify change readiness into three levels of analysis and have divided organization level readiness and individual readiness separately, similarly as Weiner (2009). The framework is presented in the figure x below

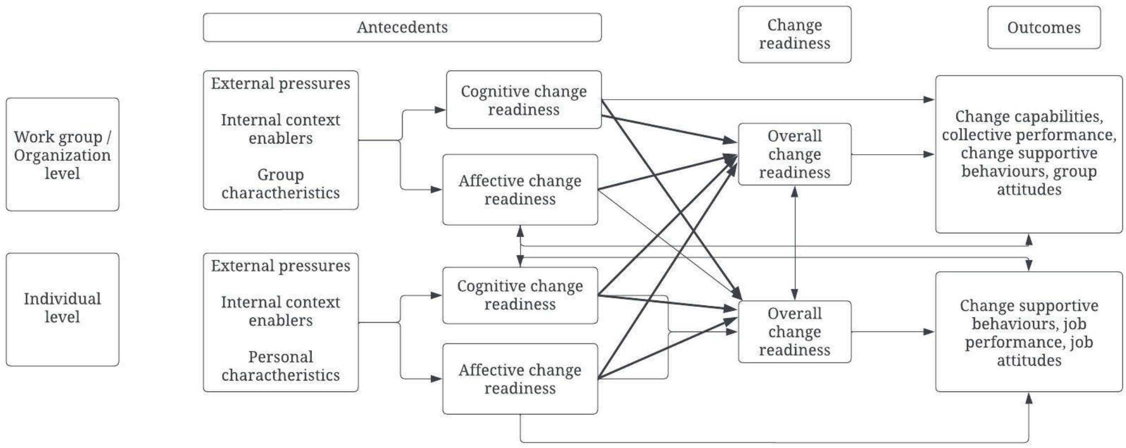

Figure 5: Multilevel Framework of change readiness (Rafferty et al. 2013)

Change readiness is a function of multiple factors and capabilities. The multilevel framework of readiness however does not include the use of new technologies, instead focuses on the personnel and other intangible capabilities of a company.

Creative accumulation and innovation readiness level

According to Sabatier et al. (2012) identifying factors that might trigger the change in the industry's value creation logic can help companies develop strategies to enable them to capture greater value from their innovations. Bergek et al. (2013) argue that companies can attain creative accumulation to answer technological discontinuities better. Creative accumulation describes innovation capability of incumbents that triumph when facing technological discontinuities. In the more commonly known process; creative destruction the innovation is not driven by the incumbents, but by the small firms and new entrants (Filippetti et al. 2009).

According to research the competitive outcome of a discontinuous innovation depends on its influence on firms' existing resources, skills and knowledge (Bergek et al. 2011, 2013). However, the study by Filippetti et al. (2009) showed that in a major disruptive crisis like the 2008 financial crisis, both patterns creative destruction and accumulation were present.

3.1 Maturity models

Maturity and readiness are synonyms at least on some level but there are differences between the two. In systems engineering maturity is encapsulated within the notion of readiness, so from this point of view they cannot be treated as separate entities and used in isolation. It could be argued that the existing readiness levels actually provide a "Maturity" metric (Tetlay & John 2009). However, Tetlay & John (2009) used maturity and readiness as two clear distinct entities in their research. They defined maturity as a verification within an iterative process and it occurs before "readiness". Readiness is defined as validation whether the system is ready or not and it required a certain level maturity. (Tetlay & John 2009) Similarly, Pedroso, Calache, Lima, Silva & Carpinetti (2017) define maturity as a development of a beginning phase to a more advanced one and maturity levels can be characterised as the evolutionary path towards a more mature process in which each level presents its own goals that need to be achieved to get a higher maturity level.

According to Akdil et al. (2018) and their review on maturity, maturity is defined as a term describing being complete or perfect. It is also used to describe the level of progression of specific abilities or capabilities to reach the aimed perfection. (Nikkhou, Taghizadeh & Hajiyakhchali 2016, Akdil, Ustundag & Cevikcan 2018) In addition, Chonsawat & Sopadang (2019) have even used maturity level to measure readiness. A mature organization can be seen as one that is competent in meeting its needs by using standardized approaches while immature organization lacks implementation of these processes. The difference between readiness and maturity can be explained in a way that models to measure readiness clarify whether the organization is ready to start development process; however models to measure maturity often target to demonstrate which maturity level the organization is in (Akdil et al. 2018, Schumacher et al. 2016, Pedroso et al. 2017).

Different methods to measure maturity have been developed to determine how well organizations are doing in order to improve their performance. Maturity model is a framework that optimizes the process and tools that could offer desired solutions. Maturity model brings tidiness to companies' strategic plans and fosters continuous improvement (Bakhtieva 2017). Maturity models allow organizations to assess and compare their practices with the intention to map our structured path to improvement and benchmark themselves to others as well as finding the best practices. (Nikkhou et al. 2016, Schumacher et al. 2016, Akdil et al. 2018, Boufim & Barka 2021) SimilarlyBakhtieva (2017) argues that there are three main purposes for maturity models:

1. Descriptive: assessing the status of processes with reference to desired goals
2. Prescriptive: providing recommendations regarding following strategic decisions
3. Comparative: used as a benchmarking tool for clear positioning on a market

One of the first maturity model: capability maturity model (CMM) developed by Paulk, Curtis, Chrissis & Weber (1993) described the maturity of software organizations. Based on CMM Cagnin, Loveridge & Butler (2005) developed a method to measure sustainability maturity with a business sustainability maturity model (BSMM), which has then been complemented by Siew, Balatbat & Carmichael (2016) fuzzy-based approach called Project sustainability maturity model (PSML). Fuzzy approach allows to measure linguistic values in the questionnaire as well. In addition there are other maturity models developed for project management that base on the CMM. Nikkhou et al. (2016) have developed a portfolio management model called ELENA. Today economic challenges are driven by rapid technological and societal development steps, this paradigm is referred to as industry 4.0 (Akdil, Ustundag & Cevikcan 2018). As transformation to the industry 4.0 has difficulties Schumacher et al. (2016) and other scholars have developed maturity models to support this transformation Erol, Schumacher & Sihn (2016). The deprecation of third-party cookies and the world without them can be seen as a Digital marketing 2.0, so a maturity model to measure the maturity in this transformation is useful and generates value for the companies using the model.

4 Maturity model development

Hirschheim, Schwarz & Todd (2006) noticed that IT-organizations are lacking relation management skills and have developed a marketing maturity model specifically for IT-organizations. Their view on maturity level is valued based on marketing mix, success and strategy. The levels they present are competency, credibility, and commitment. Interestingly their marketing maturity model is the only one presenting a suggested time frame for reaching the specific maturity level.

Bakhtieva (2017) has researched the existing Digital Marketing Maturity Models (DMMM) that were accessed free of charge online. The models over viewed and compared in the research were Adobe's Maturity Self-Assessment tool (ASDT), Digital Marketing Maturity Index (DMMI) by Stein IAS and Oracle marketing cloud, and the Smart Insights Digital Marketing Toolset (SMART) by web-portal Smart Insights. Based on their SWOT-analysis on DMMMs, Bakhtieva (2017) suggests the structure of a B2B digital marketing maturity model presented in figure 6:

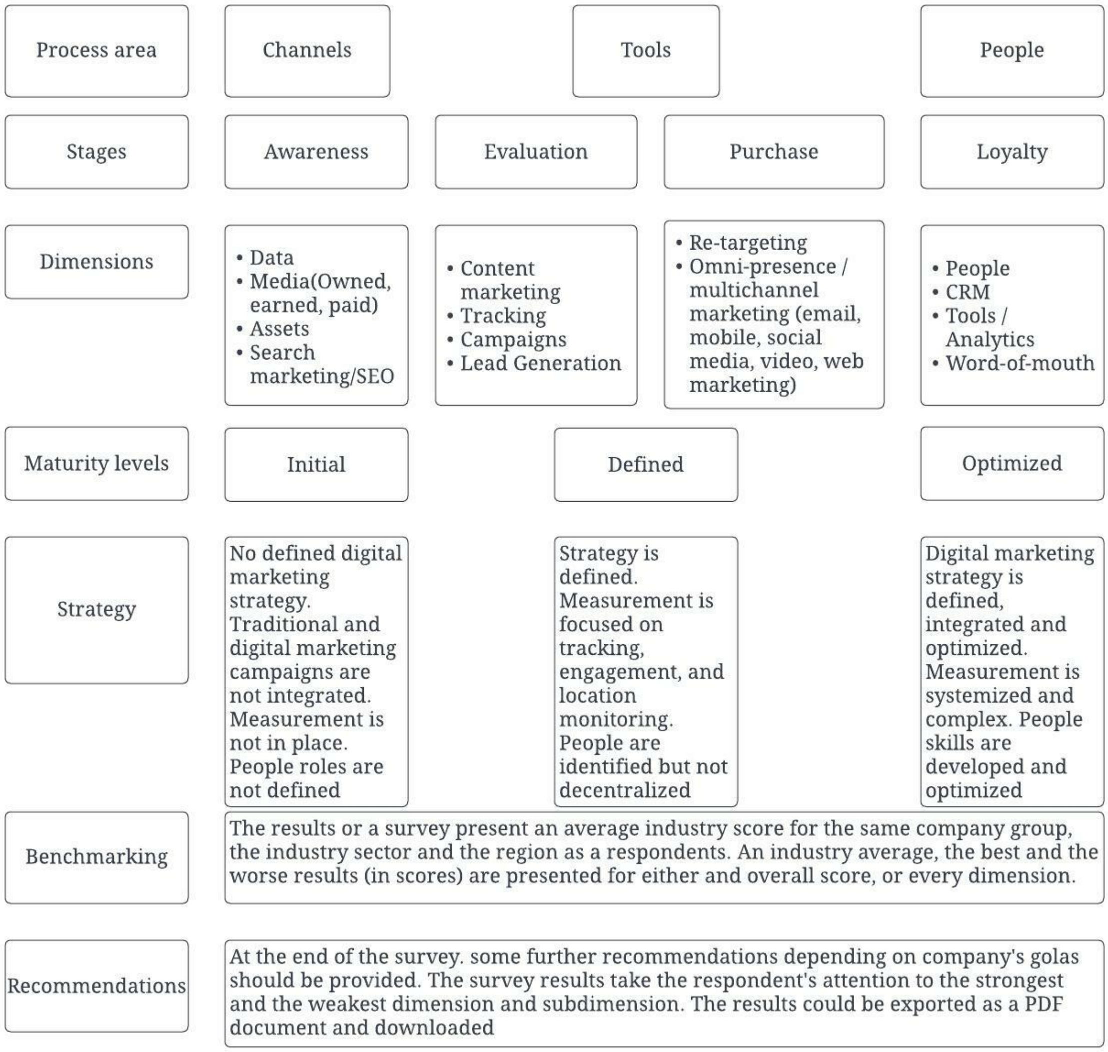

Figure 6: The structure of a B2B digital marketing maturity model (Bakhtieva 2017)

Similarly like Bakhtieva (2017) Rossmann (2018) studied digital marketing and digital maturity measurement conceptualization, they found that the concept of digital maturity incorporates eight capability dimensions dealing with strategy, leadership, business and operating mode, people, culture, governance, and technology.

In Boufim & Barka (2021) digital marketing context maturity is characterized by the overall absorption of digital marketing concepts. They propose five stages of growth, instead of three maturity levels like Bakhtieva (2017) suggested. These five staged are presented in the figure 7:

Figure 7: Five stages of the maturity model (Boufim & Barka 2021)

In the first stage a company does not have any official frame to orchestrate digital marketing. This stage is characterized by experimentation. In the expansion stage the management is aware of the potential of the digital marketing implementation. In formalization stage the digital marketing strategy is formalized, communicated, and approved. Integration stage is where the marketing strategy evolution is integrated into the overall strategy of the company. In this stage a 360 view on customer is provided and centralized for predictive decision making. In the final stage company is mature. The Return On Investment (ROI) and customer costs as well as conversions are continuously challenged. Continuous improvement is implemented to keep pace with digital environment and anticipate the challenges of a continual changing environment. (Boufim & Barka 2021)

Probably one of the most novel maturity models is developed by Seebacher (2021). Seebacher's model has five stages: (1) One directional, reactive marketing, (2) Bidirectional, reactive marketing, (3) Interactive marketing, (4) Proactive analytics marketing and (5) Predictive profit marketing. The model is presented in the figure 8:

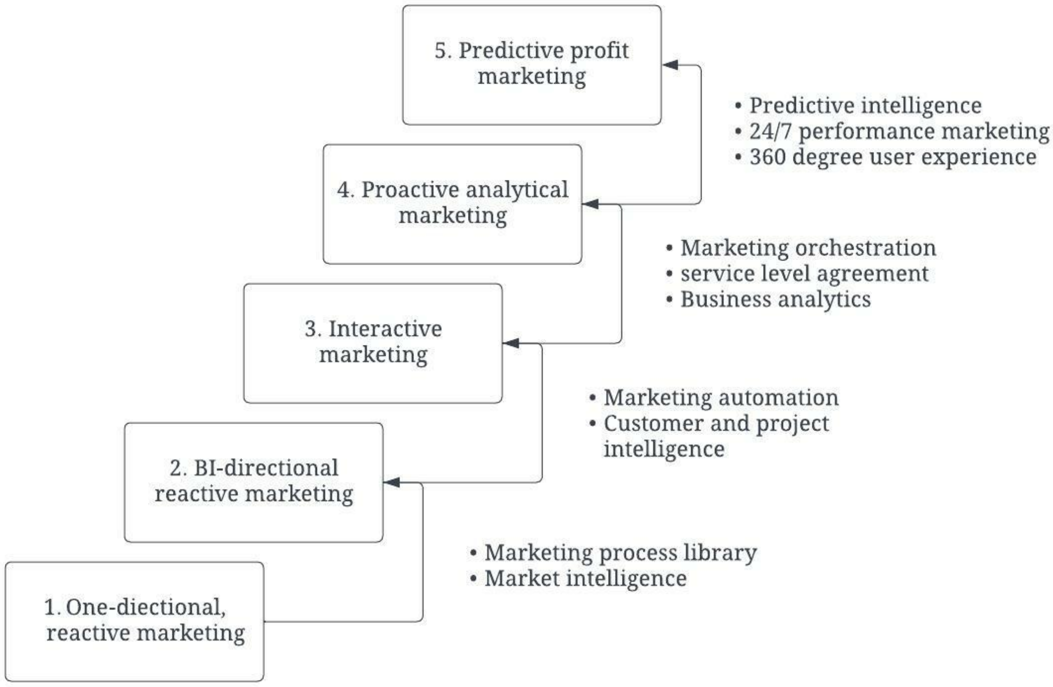

Figure 8: Five stages of the maturity model (Seebacher 2021)

One-directional and reactive marketing can be defined as the stereotypical industrial goods marketing, where direction of the respective communication is one-directional. Based on the one-directional the logical consequence for the next level is that the marketing is reactive. The second stage in the model is Birectional reactive marketing. If marketing was only the recipient of information at the first stage of maturity, the position changes in this phase to communication in both directions—toward marketing but also from marketing into the organization. Third stage in the model, interactive marketing is characterised by the integration of marketing in more and more operational areas of the companion, who is involved in activities from the beginning in order to benefit from expertise. However, interactive marketing also means that new impulses are constantly being given by marketing with the aim of making the potential of modern B2B marketing available to the company step by step. In the fourth stage Proactive analytics marketing is increasingly developing an understanding of things that work better and those that should be optimized as the pool of data is growing. In fifth stage Predictive profit marketing the performance marketing activities will enable the organization to define exactly who, where, how, and what has attracted which customer. (Seebacher 2021)

Hoogveld & Koster (2016) and Moi & Cabiddu (2021) have both developed and studied agile marketing maturity models and frameworks. In marketing, agility means "the degree to which a firm can sense and respond quickly to customer-based opportunities for innovation and competitive action (Moi & Cabiddu 2021). According to Hoogveld & Koster (2016) the most suitable way to measure company's marketing agility is *Objectives-Principles-Starategies (OPS)* framework. It is an approach to determine how capable an organization is in providing supporting environment to implement an agile method, and to determine how effective the implementation of the agile method is in achieving its objectives. In other words, it is an hierarchical or iterative process where the preconditions need be in good shape before something can be implemented. Other way to think would be that the objectives are the dimensions, principles are sub-dimensions and strategies are the "sub-sub-dimensions". The objectives in the OPS framework are (Hoogveld & Koster 2016):

- Human centric
- Value driven
- Minimal waste
- Maximal adaptability
- Continuous innovation and learning

Worth noticing here is that the OPS framework is not specifically developed for marketing context, but according to Hoogveld & Koster (2016) this is the best suited method for adaption to an agile maturity model.

The agile marketing maturity model and its dimensions developed by Moi & Cabiddu (2021) have many similarities with OPS framework:

- Customer oriented responsiveness
- High Flexibility

- Human collaboration
- Quick and continuous improvement

Organizations with high customer oriented responsiveness maturity have integrated different technologies and engage in inbound marketing, while studying proactively their target customers and understanding to promote their offering through using digital means and creating ad hoc campaigns. A mature company with high flexibility undertakes more proactive actions to adapt their marketing performance to new conditions with methods like experimentation. High level of maturity in human collaboration means a high level degree of human collaboration across teams and departments. In addition, these organizations exhibit active participation of people in decision-making and are always ready to address unexpected problems. Organizations that have high maturity level in quick and continuous improvement regularly employ proper qualitative and quantitative evaluation techniques and define more structured qualitative and quantitative goals. These organizations are committed to continuous marketing planning and monitoring. (Moi & Cabiddu 2021)

However, many of the current marketing maturity models are developed by consultancies and other marketing ecosystem parties. Their own maturity models regarding digital marketing as well as privacy and digital transformation. For example Microsoft has their own maturity model which focuses on privacy. Gooogle in partnership with Boston Consulting Group (BCG) have developed a Digital maturity benchmark survey, which measures companies maturity on digital marketing. Both which are used but only have few questions or capabilities related to the deprecation of third-party cookies. (Microsoft 2022, Google 2022)

Forrester's Gill & VanBoskirk (2016) have developed a four level maturity model but their focus is on digital transformation in general. So it is quite similar as the models from Akdil et al. (2018), Schumacher et al. (2016), Erol et al. (2016), Chonsawat & Sopadang (2019) which focused on Industry 4.0. According to Gill & VanBoskirk (2016) there are four different dimensions that determine Digital Maturity these are presented in figure 9:

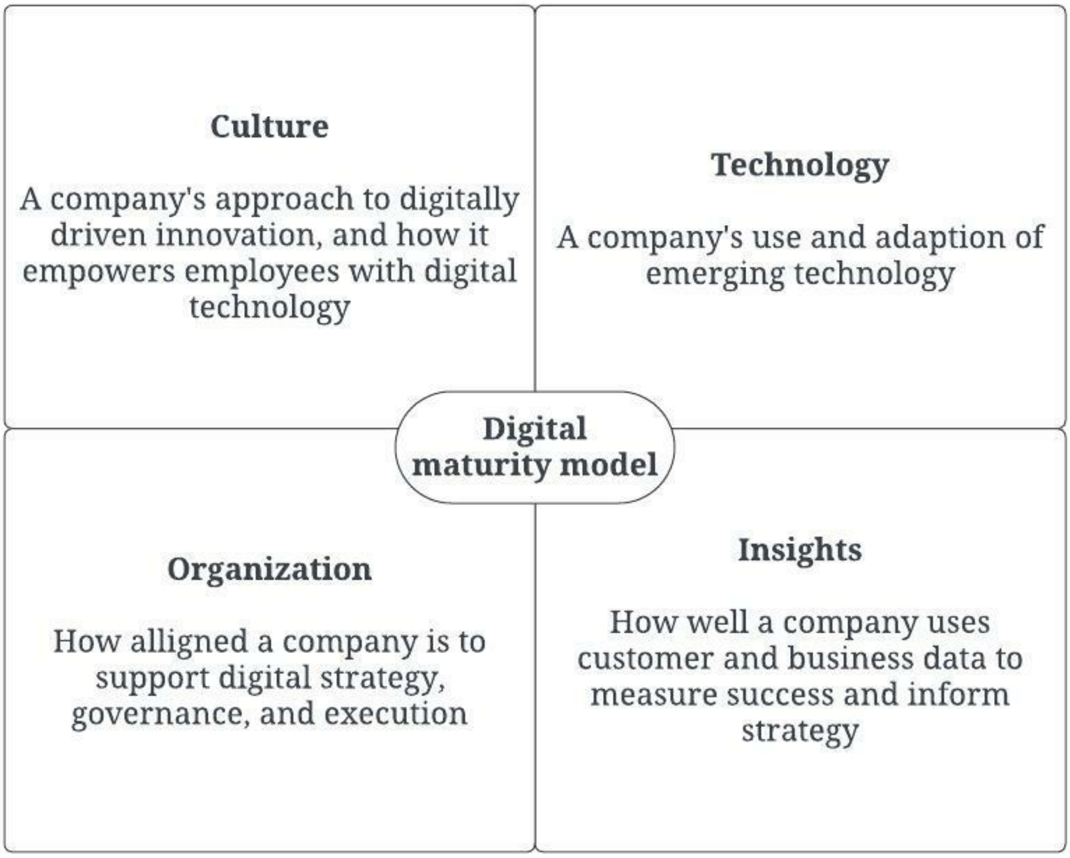

Figure 9: Four dimensions to determine digital maturity (Gill & VanBoskirk 2016)

BCG also conducted a survey about B2B marketing in a world without cookies in collaboration with LinkedIn, which revealed that data privacy questions raise concerns in marketers and also that majority of the answer to the survey were not fully prepared for the data privacy shifts (Dewey, Ratajczak, Kilborn & Shrivas 2022). According to Field, Patel & Leon (2018), Rogers, Moiño, Leon & Poncela (2021) there are six enablers that promote digital marketing maturity:

- **Technical enablers**
  - Connected data
  - Actionable measurement

  - Automation and integrated tech
- **Organizational enablers**
  - Strategic partnerships
  - Specialist skills
  - Agile teaming and fail-fast culture

Rogers et al. (2021) argue that there are four different accelerators that have become primary determinants of digital marketing maturity:

- Build a virtuous cycle around first-party data in order to address privacy concerns and maintain customer value and trust
- Develop a true end-to-end measurement capability that includes predictive models to replace data from third-party cookies
- Set up agile performance loops based on test-and-learn approach break down silos and be better prepared to address future demand volatility
- Secure new skills and resources to help ensure continuous improvement

In Microsoft (2022) guide to Privacy maturity, the key topics for digital maturity in privacy context are: (1) First-party data, (2) Data managements, (3) Partners and publishers. Both BCG and Microsoft present four level maturity model. Adobe (2021) has also conducted a survey related to digital marketing maturity and privacy. In Adobe's survey they found four solutions that could resolve challenges with readiness: (1) First-party data ecosystem, (2) New features in web browsers, (3) Data clean room and (4) Contextual advertising. Adobe's survey also found five strategies for cookieless future readiness:

1. Implement new technology
2. Secure alternatives for third-party profile enrichment
3. Internal awareness/education
4. Begin leveraging more durable identifiers

5. Create second-party data relationships

From these strategies the implementation of new technologies received the most votes and create second-party data relationships the least. These results are some what similar to capabilities listed Microsoft's and BCG's maturity model, all though the implementation of technology was not emphasized in the aforementioned models, surprisingly creating relationships was not as emphasized in Adobe's survey. However, all of the three companies agree that First-party data is a major factor in digital marketing maturity. A marketing maturity model developed by MightyCitizen (2022) does include a section about technology but the model itself is more focused on marketing in general rather than digital marketing and privacy.

Similarly all the models presented above put value on data and specifically on the "right" data, however they take "softer" like organizational and personnel aspects along and not necessary focus on "harder" attributes or capabilities. In addition many of the models like the one presented by Seebacher (2021) are on a higher, more general level than what the purpose of thesis, which is just to focus on third-party cookies.

4.1 Building the maturity model

As the goal of this thesis is to build a quickly usable tool to measure maturity, the maturity model we are using as base is the mode developed by Siew et al. (2016). They developed a tool to quickly measure the sustainability maturity level in project management based on fuzzy logic. A fuzzy-based approach and its many variations have been widely used to capture the subjective perceptions of experts across different industries(Siew et al. 2016). A fuzzy-based approach is advantageous compared to other approaches because it does not require large amounts of data such as in fault/event, decision and probability trees and Monte Carlo simulation, and more closely resembles human perception (Siew et al. 2016, Pedroso et al. 2017). The fuzzy-based approach is robust and easy to understand (Siew et al. 2016).

Based on the literature review on third-party cookies and the maturity models reviewed there are three dimensions in our maturity model:

1. First party data - Development of own data capabilities
2. Targeting
3. Develop marketing measurement

Based on the level of these three dimensions we can interpret what is the company's maturity for third-party cookie deprecation. The dimensions follow similar logic as OPS presented by Hoogveld & Koster (2016), here the First-party data would be considered as *Objective*, targeting would be considered as *principle* and develop marketing measurement would be the *strategy*. However, in our model these are not presented in a hierarchical way as they all play a major role in maturity in a world without third-party cookies. The Third-party cookieless maturity model developed is presented in figure below and the corresponding dimensions and sub-dimensions are elaborated in their own sections:

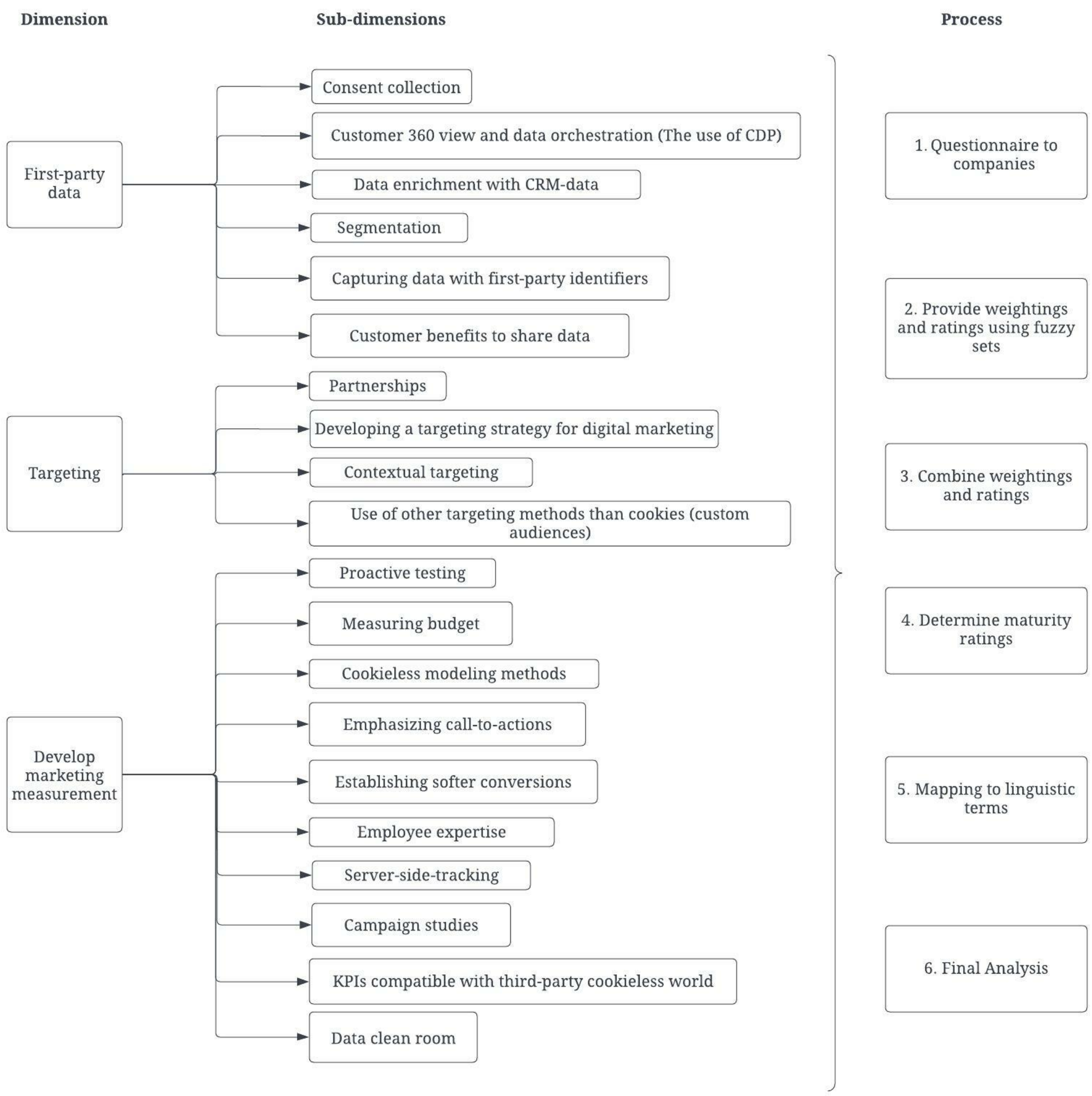

Figure 10: Third-party cookies maturity model

For each sub-dimension five levels of maturity are proposed: (1) Very Low, (2) Low, (3) Fair, (4) High, and (5) Very high. The sub-dimension maturity levels are then aggregated to the corresponding dimensions which are then aggregated to the final maturity levels, which are further presented in section 4. The model presented in this thesis is not meant to represent an all-encompassing list of areas related to third-party cookieless maturity. As the literature and academic research on third-party cookies deprecation and the paradigm shift in digital marketing attached to it becomes more mature, new dimensions and sub-dimensions can be added or the existing ones can be removed.

4.1.1 First-party data

According to Seebacher (2021) long and successful marketing occupies professional data management. IAB (2022*a*) suggested companies to gain maximum value on first-party data rather trying to replicate or find a "work around" for third-party cookies. Finding other ways to track consumers with first-party data is vital. First-party data is also more resilient for cookie countermeasures(Demir et al. 2022). Over 40 percent of the respondents to the IAB (2022*b*) have increased spending and emphasis on the use of first-party data. The survey by Adweek (2020) had similar results as over 60 percent of the respondents have undertaken first-party data strategies to counter third-party cookie deprecation.

Companies need to make sure that the data is collected responsibly and transparently via Consent management platform. Furthermore, the consent needs to be collected in the first place, which is why the companies need make it easy for consumers to see the benefits they receive when they share data with the company. For example, Jai & King (2016) found that loyalty programs can increase the willingness to share their data on some consumers. Similarly, the survey by Adobe (2021) found out that over half of the consumers were willing to share data for certain incentives. IAB (2022*a*) also argues that the benefits about the data sharing need to be transparent. This is especially important as the first-party data should be more persistent than just Cookies. For example, email registry and CRM are important. Furthermore, the survey by LiveIntent (2021) shows that respondents think that email address and publisher first-party data, alongside with universal ID are the best candidates to replace third-party cookies.

According to IAB (2022*a*) there are clear and distinct benefits to work with email and CRM data, instead of cookies:

1. Cookies only last for 7-30 days when email addresses are often used for several years. This means that data can be stored and accumulated over time.

2. Email address as a identifier is platform agnostic, unlike third-party cookies which is domain and platform specific.

3. Giving durable identifiers like email give the advertiser a "gold" standard consented approved to use marketing data. In other words it is more acceptable to advertise to someone whose email you have received from the owner instead of a cookie.

All this data needs to be collected, managed and activated in Customer Data Platform (CDP), where data from multiple sources is unified into a customer profile (CDPInstitute 2022). This allows companies to personalize the digital customer experience and stay compliant with data privacy regulations (Microsoft 2022). CDP enables a 360 view on the customer and centralized data orchestration, which is one of the features in the integration stage in Boufim & Barka (2021) digital maturity model. A survey by Adweek (2020) shows that the most undertaken measure the respondents had taken to counter the impact of the deprecation of third-party cookies is Building a CDP. As noted multiple times in this report, prior literature and above presented maturity models; data privacy is the key to survive in the world without cookies. Consumers have more rights than ever to control how their personal data is used and they are increasingly aware of them. The need to comply with transparency, consent and personal data processing obligations does not end with the deprecation of third-party cookies (IAB 2022*a*). That is why more than few of the sub dimensions overlap with each other as they are used to increase the data privacy capabilities. All in all, data privacy regulations initialized the removal of third-party cookies.

To understand the need to enrich CDP data with CRM data, the difference between the two should be defined. CRM systems are good for creating customer records for individuals who are already known to your brand and have entered sales funnel. However, it does not capture all the unknown individuals who interact with the brand throughout the entire customer journey. CDP systems are designed for marketing teams to manage the end-to-end customer experience, starting with the very first touchpoint with the brand before they are identified. (CDPInstitute 2022)

One of the sub-dimensions in first-party dimension is segmentation which overlaps a little bit with the *Targeting* sub-dimensions. For example the generation of custom audiences and the use of other cohort targeting methods become much easier when the customer segmentation is already comprehensive. In addition, first-party data enrichment with CRM data becomes easier when the customer segments are already comprehensive.

4.1.2 Targeting

As behavioral targeting is not going to be available in the future, companies need to find new ways to target, which is why targeting is added as one of the three main dimensions. Collaborating with mediums and publishers and proprietary platforms will enable cross-platform tracking even when third-party cookies are gone. A partnership with a medium also enriches the custom audiences and other cohort methods advertisers should be using instead of cookies, which we talk about later. Collaboration and partnerships were the dimension almost all the digital maturity and privacy models had in common and partnerships in general are one of the sub dimensions in this model. Furthermore, the survey results from IAB (2022*b*) also indicate that companies are interested in partnerships; 42 percent of the respondents are expanding their engagement with third-party industry groups seeking to build ”post-cookie” identity resolution solutions. In addition, over 80 percent of the respondents in LiveRamp (2021) survey are currently or are planning to collaborate with a third-party to share first-party data for insights, activation, measurements, or attribution.

The marketing strategy is highly related to the level marketing maturity in both Boufim & Barka (2021) and Bakhtieva (2017) models. As the shift away from behavioral targeting is the important removal effect of third-party cookies, we could argue that having a good targeting strategy to answer this shift is a major contributor for company's maturity. They way this sub-dimension is measured in our model is based on the maturity model from Boufim & Barka (2021). Related to the targeting strategy. Contextual targeting is added to our model as separate sub-dimension because contextual targeting or advertising does not require the use of tracking techniques and that is why it is vital for companies to utilize when behavioral targeting is not possible.

Contextual targeting in the model is only measured superficially as the success of contextual advertising might not be in the hand of the advertiser. As noted before the performance of the contextually targeted ads depends on the web page as well as the computation capabilities of the ad server (Anagnostopoulos et al. 2007). In addition, a survey results from IAB (2022*b*) show that over 40 percent of the respondents have increased spending and emphasis on contextual advertising and the results from Adweek (2020) tell that over 50 percent of respondents have moved to contextual targeting strategies.

The use of other targeting methods than cookies in this models means the level how well companies have utilized cohort marketing methods like custom audiences (Block 2021). Custom audiences do require enough first-party data to be generated so only a company with high maturity in first-party dimension can use custom audiences effectively. According to Block (2021) cohort segmentation is a reasonable solution to privacy problems, but there are few significant issues regarding the cluster methodology to create the cohorts, the size of cohorts and the heterogeneity of the cohorts. This sub-dimension could be altered in the future because a good share of respondents in IAB (2022*b*) have increased interest in building or seeking a "post-cookie" identity solution either in-house or with assistant of the third-parties. Furthermore, over 60 percent of the respondents on Adweek (2020) survey are also building out a private ID graph to tackle the deprecation of third-party cookies. Additionally, Statista (2020*a*) forecasts the spend in identity solutions to increase from 3 billion to 4.1 billion euros in Europe over 2022-2024, the figures in the same period in the U.S. are 5.73 billion to 8.2 billion dollars. However, companies should focus on identity solutions that are compatible with the data privacy regulations.

4.1.3 Develop marketing measurement

Marketing measurement is not going to be the same anymore and some key performance indicators (KPIs) are going to become obsolete (IAB 2022*b*). From the IAB (2022*b*) survey's results it can be interpreted that measurement is the function where approaches are incomplete, when at the same time the ad campaign measurement and the aforementioned attribution modeling are going to be the most affected areas by third-party cookie deprecation according to respondents. Hence, develop marketing measurement is added as one of the dimensions in our model.

As measuring user behaviour becomes more difficult, the measurement should be guided more towards environment based measurement like sites, ad placements, devices and formats. Most of the display advertising conversions are called view through conversions, which that the user has seen the ad but did not click it before the conversion. In the future these conversions cannot be tracked, leaving most of the display advertising conversions untraceable. Novel methods to measure marketing performance are required and some have already been developed. For example the aforementioned attribution modeling will demise since it is based on the paths of cookies IDs of a user of both click and view through conversions. Having right metrics to diagnose the measures suitable for improving performance is a key capability required for analytics-driven performance (Chaffey & Patron 2012). A cookieless statistical method like marketing mix modeling, where marketing activities over time are linked into a dependent variable should be utilized. However, the marketing mix modeling modeling can be expensive and require a vast amount of data (Tellis 2006, Wolfe Sr & Crotts 2011). One could argue that a good option would be optimizing the campaigns via clicks. However, throughout the times of digital marketing clicks have been a bad way to optimize campaigns. Better answer here would be to create a softer click-through conversion. In addition, the importance of call-to-actions (CTAs) in ads will be emphasized in the third-party cookieless world. This is in line with the results from Goldfarb & Tucker (2011) which said that the less targeted the ad is the more obtrusive it can be.

Many of the aforementioned models included various softer dimension related to personnel and organization like the one from Rossmann (2018). In addition, the other aforementioned theories of readiness argue that the readiness is a function situational and contextual factors like company culture and resources, and successful implementation is a function of readiness. In our model these factors are included in this dimension with the measurement budget, testing and employee expertise sub dimensions. If there is a solid budget for marketing measurement it can be interpreted that the management supports measuring actions. The main barriers for improving digital marketing performance are the lack of resources and budget (Chaffey & Patron 2012). Also according to IAB (2022*b*) measurement is a multi-billion-dollar problem. In addition, if the company does testing well, we can assume that they are agile and own a fail-fast culture and quick and continuous improvement, which was one of the building blocks as well as accelerator for digital maturity in Rogers et al. (2021) model and one of the dimensions in Moi & Cabiddu (2021) agile maturity model. In addition, different testing methods are the most used methods to improve conversion rates, systematic testing is also sign of high web analytics maturity (Chaffey & Patron 2012).

Data clean rooms are safe spaces where insights from different platforms are commingled with first-party data from marketers for measurement and targeting. Data clean rooms are used by business to better understand their advertising data and create custom audiences to use for advertising purposes with privacy measures in place. This means that the personally identifiable information is anonymized, processed and stored in a privacy-compliant way (IAB 2022*a*, Microsoft 2022). Because collecting data appropriately is a key for rich first-party data, use of clean rooms is one of the sub-dimensions in the maturity model. Getting a data clean room also arose as one of the top five countermeasures for the impacts of third-party cookies deprecation in Adweek (2020) survey.

Because the online traffic is not going anywhere a functional web analytics is required. Web analytics could be one of the dimensions listed in our model, but as it is such a large entity we have narrowed it down to few separate dimensions. In theory, the benefits of web analytics are clear, however, according to Järvinen & Karjaluoto (2015) the benefits of exploiting web analytics remains unclear. Nevertheless, based on the maturity models presented above, a mature digital marketer measures their marketing actions' performance. Therefore web analytics maturity related to third-party cookies is measured with the questions regarding transferring away from Universal Google Analytics and the utilization of server-side tracking as well as data clean rooms. Google has announced that Universal Google Analytics will sunset in 2023 and the compatibility with the current data regulations of it is questionable.

Currently most of the websites trigger tracking in on client-side (Schmucker 2011).

Server-side tracking on the other hand has few benefits in addition to being the modern solution over Client-side tracking. In server-side-tracking all data is collected with one tracking script. Data is collected with first-party cookies so the data can also be collected after the third-party cookies are gone. When server-side-tracking is used most of the tracking scripts are not included in the website's code which means that the site downloads faster. Server-side-tracking grants the tracker the option to choose what data is sent from the tracking server to the advertising management platforms.

5 Data and methodologies

In this chapter we going through the factors, the nature of the material used and the research methods. The material is collected via questionnaire similarly as in Siew et al. (2016) research. The questionnaire is build based on our model presented above. The triangular fuzzy numbers are build based on the answers on the questionnaires.

5.1 Fuzzy sets

Fuzzy sets are defined as a "class of objects with a continuum of grades of memberships" (Zadeh 1965). Fuzzy logic differs from classical logic due to its ability to allow certain objective to be partially included in more than one set at the time (Pedroso et al. 2017). Similarly as Siew et al. (2016) and Pedroso et al. (2017) this thesis uses triangular memberships. The definitions of these are given in the next section. Using fuzzy sets to value Digital marketing maturity level adds value to this research as it is not a straightforward process to valuate companies digital marketing capabilities comparably due to the company sizes, needs, and resources. That is why having a subjective perception is important and fuzzy-based approaches and its variations have been widely used to capture it (Siew et al. 2016). All the answers in the questionnaire and eventually the maturity rating depends on the personal opinion, and fuzzy sets are suitable technique to address this kind of issue (Pedroso et al. 2017). Subjectivity adds impreciseness to information and according to Klir & Yuan (1995) and Pedroso et al. (2017) fuzzy sets can serve as a precise way for dealing with imprecise information. In addition, when developing soft computing, which fuzzy logic represents, Zadeh (1965) wanted it to be tolerant of imprecision, uncertainty, and partial truth. As the questionnaire used in this thesis is based on linguistic variables and fuzzy logic is a suitable way to quantify linguistic terms as fuzzy numbers (Klir & Yuan 1995).

5.1.1 Fundamental definitions

Fuzzy sets

A Fuzzy set A in X (where X is a collection of object denoted by x) is given by a membership function $f_A(X)$ which represents the grade of membership of x in A (Siew et al. 2016). The nearer the value is to unity (given by 1), the higher the grade of membership is. There are many different functions for characterising fuzzy numbers, for example linear, nonlinear and exponential functions (Siew et al. 2016, Pedroso et al. 2017). From the linear functions the triangular fuzzy membership function is simple and is able to serve its purpose well (Pedroso et al. 2017). According to Siew et al. (2016) there are three relevant definitions pertaining to triangular fuzzy membership.

Definition 1: A triangular fuzzy number with number member x, denoted x (a_1, a_2, a_3) has the following membership function (Siew et al. 2016, Klir & Yuan 1995, Pedroso et al. 2017)

$$\wedge(x; a_1, a_2, a_3) = \begin{cases} 0, & x < a_1 \\ \frac{(x-a_1)}{a_2-a_1} & a_1 \leq x \leq a_2 \\ \frac{(a_3-x)}{a_3-a_2} & a_2 \leq x \leq a_3 \\ 0, & x > a_3 \end{cases} \tag{1}$$

where a_1, a_2 and a_3 denote lower limit value, mean value and upper limit value respectively.

Algebraic operations and fuzzy numbers

Definition 2: if there are two fuzzy numbers A and B parameterised by the triplets (a_1, a_2, a_3) and (b_1, b_2, b_3) then the operations of a traingular fuzzy number can be expressed as (Siew et al. 2016)

$$A(+)B = (a_1, a_2, a_3) + (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{2}$$

$$A(-)B = (a_1, a_2, a_3) - (b_1, b_2, b_3) = (a_1 - b_1, a_2 - b_2, a_3 - b_3) \tag{3}$$

$$A(X)B = (a_1, a_2, a_3)X(b_1, b_2, b_3) = (a_1b_1, a_2b_2, a_3b_3) \tag{4}$$

Definition 3: The distance between triangular fuzzy numbers A a_1, a_2, a_3 and B (b_1, b_2, b_3) can be computed based on a geometrical interpretation given by,

$$D(A, B) = \begin{cases} (\frac{1}{3} \sum_{i=1}^{3} |a_i - b_i|^p)^{\frac{1}{p}} & 1 \le p \le \infty \\ max(|a_i - b_i|) & p = \infty \end{cases} \tag{5}$$

If p=2, this reduces to a Euclidean distance measurement, which is the most commonly used for distance measurement in triangular fuzzy numbers. If for example, A and B are two real numbers where $a_1 = a_2 = a_3 = a$ and $b_1 = b_2 = b_3 = b$, the distance between them is similar to a Euclidean distance calculation (Siew et al. 2016).

$$\begin{aligned} D\left(A, B\right) &= \sqrt{\frac{1}{3}[\left(a_1 - b_1\right)^2 + \left(a_2 - b_2\right)^2 + \left(a_3 - b_3\right)^2]} \\ &= \sqrt{\frac{1}{3}[\left(a - b\right)^2 + \left(a - b\right)^2 + \left(a - b\right)^2]} \\ &= \sqrt{(a - b)^2} \\ &= |a - b| \end{aligned} \tag{6}$$

5.2 Fuzzy-based approach

The dimensions and sub-dimensions measured are presented in the figure x. For each sub-dimension four levels of maturity are: "ad hoc","defined", "managed", and "integrated". The maturity levels and their corresponding fuzzy set numbers are listed in table 1:

Table 1: Maturity level rating and corresponding triangular fuzzy numbers

Maturity level rating	**Triangular fuzzy number**
Ad hoc (AH)	(0,0,0.3)
Defined (D)	(0.1,0.3,0.5)
Managed (M)	(0.5,0.7,0.9)
Integrated (I)	(0.9,1.0,1.0)

Ad hoc level represents a stage very companies have taken minimal actions irregularly. In Defined level companies are starting to take action. Minimum viable actions to survive have been taken, but for example implementation of performance measurement is not done. In Managed level companies are collecting consent accordingly and storing it in a centralized location. A clearer strategy for targeting and data is designed. Companies are using other targeting methods, measurement is done and the results are implemented but they are not yet integrated part of companies' day-to-day actions. Integrated level companies separate each other from the managed companies by doing testing and measuring continuously. This enables companies to be truly data-driven and base their decisions of real data as the KPIs and conversions are set compatibly with the demise of third-party cookies. In addition, Integrated companies have been able to collect a vast amount of first-party because there are clear benefits for customer to share data with them. A more detailed description of the levels is shown in Appendix A.

Siew et al. (2016) also used weights of each of dimension to valuate the final maturity level, which were also computed following the characteristics of fuzzy sets. Practically this means that after measuring the maturity level of each sub-dimension the person who answers is asked how important the specific sub-dimension is for them. This kind of approach allows the derivation of both maturity level rating and normalized maturity level rating, which is elaborated later. By manipulating the distance measurement of triangular fuzzy numbers, the normalized maturity level rating can be mapped to a suitable linguistic term, which reflects the degree of maturity (Siew et al. 2016). The weightings and corresponding triangular fuzzy numbers are presented in the table 2:

Table 2: Weightings and corresponding triangular fuzzy numbers

Weighting	**Triangular fuzzy number**
Very low (VL)	(0,0.1,0.3)
Low (L)	(0.1,0.3,0.5)
Fair (F)	(0.3,0.5,0.7)
High (H)	(0.5,0.7,0.9)
Very high (VH)	(0.7,0.9,1.0)

If there would be more than a one person assessing company's maturity level, average fuzzy ratings and average fuzzy weightings for the maturity level criteria can be used similarly as Siew et al. (2016). Both average fuzzy ratings and weightings are given as:

$$S = \frac{1}{n}\sum_{i=1}^{n} s_i \tag{7}$$

$$W = \frac{1}{n}\sum_{i=1}^{n} w_i \tag{8}$$

Where S denotes the average fuzzy rating, W denotes the average fuzzy weighting. s denotes the fuzzy raging for a sub-dimension, w denotes the fuzzy weighting for sub-dimension, and i denotes a person answering the questionnaire. Combining equations (1) and (2), a fuzzy maturity rating can be established.

$$TPCMLRating = \sum_{i=1}^{n} WS \tag{9}$$

The third-party cookieless maturity level (TPCML) rating is a triangular fuzzy number. To maintain the rating withing the [0,1] range, normalization is required. Siew et al. (2016) has done it in way that the maturity level rating is divided with maximum upper limit value. If the maturity level rating $= (P_1, P_2, P_3)$ and $a*$ is the the maximum upper limit value, the normalized rating is calculated using,

$$NTPCMLrating = (\frac{P_1}{a*}, \frac{P_2}{a*}, \frac{P_3}{a*}) \tag{10}$$

The normalized maturity level rating can be mapped to an appropriate linguistic term. This set is called a natural language impression set (Tan, Shen & Langston 2011). The technique used to map the fuzzy ratings with linguistic terms in this thesis is the same as in Siew et al. (2016) research. The fuzzy rating is mapped to linguistic term from a natural language expression set. The distance formula given in equation 6 is the most intuitive because it captures the subjective perception of proximity. The distance between normalized maturity level rating and each member of the natural language expression set from table 3 can be computed and the maturity level is determined using the linguistic term which gives the smallest distance. The natural language expression set is presented in the table 3:

Table 3: Natural language expression set

Natural language expression set for maturity	**Triangular fuzzy numbers**
Very Low (VL)	(0,0.1,0.3)
Low (L)	(0.1,0.3,0.5)
Fair (F)	(0.3,0.5,0.7)
High (H)	(0.5,0.7,0.9)
Very High (VH)	(0.9,1.0,1.0)

5.3 Questionnaire building

Siew et al. (2016) did not utilize or present a questionnaire per se in their research. However, they suggested that the sub-dimensions presented could be altered into more answer-friendly questions. As the data is collected from companies, making answering to the questionnaire as easy as possible is important for receiving as much data as possible. In our model all the questions are set on a linear scale from one to five, instead of a scale from one to seven like in Siew et al. (2016) research. Researches have shown that the scale from one to seven works better instead of one to five, when the cognitive capabilities of the respondent are high (Weijters, Cabooter & Schillewaert 2010, Pearse 2011, Revilla, Saris & Krosnick 2014). In addition, Revilla et al. (2014) suggest that researchers should offer scale from one to five because it yields to better data quality than larger scales. However, their research only focuses on agree-disagree -questions.

On the other hand Pearse (2011) argue that in general higher scale granularity yields more precise data. Pearse (2011) has also listed advantages and disadvantages in the scale granularity levels and the main advantage that lower granularity has is the quicker answering, which is what we need considering the goal of this thesis: developing a quick tool to assess maturity. Each answer is coded into a triangular fuzzy number similarly as Siew et al. (2016).

As noted earlier, there is a level of subjective when it comes to digital marketing capabilities, which is why it is not practical to have a one single value to represent maturity. Rather, the assessor may find the use of linguistic terms easier for expressing opinions. As well, linguistic expressions such as 'very important', 'important', 'moderately important', 'less important' or 'least important' can be used to express criteria weighting. The use of such linguistic expressions can be associated with fuzzy set membership (Siew et al. 2016, Wang 2010). However, some of the more technical sub-dimensions where maturity is measured more specifically, whether the company uses a certain technology or not, the answers are formed differently. This means that the answers are not presented in a typical likert-scale from one to five, but with a multiple choice that is presented in a linear way. The choices and questions are based on the literature view presented above and the maturity levels listed in appendix A. In addition, the questionnaire as a whole is presented in the appendix B.

The questionnaire had few questions determining few pieces of demographic information. The companies' headquarter location was asked, as well as the company size. In addition, a question about their current awareness of how third-party cookies are used in their marketing. The demographic statistics are shown in table 4.

Table 4: Demographic statistics of the survey

Company	**Company size**	**Location**	**Third-party cookie awareness in own marketing operations**
Company1	500+	Europe	Aware
Company2	50-249	Europe	Fairly aware
Company3	500+	Europe	Very aware
Company4	500+	Europe	Very aware
Company5	259-499	Europe	Aware
Company6	500+	Europe	Aware
Company7	500+	Europe	Aware
Company8	500+	Europe	Aware
Company9	259-499	Europe	Very aware

Some of the questions were presented in a typical liker scale from one to five where one meant very low and five very high. Some of the questions regarding sub-dimensions that require more specific actions from companies to reach a certain maturity level. This kind of sub-dimensions were: Consent collection, customer 360 view and data orchestration, targeting strategy, establishing softer conversions and server-side-tracking. Some of these sub-dimensions are also quite new and companies might even know what kind actions they should take to rate themselves good at it.

6 Results

The study followed the steps presented in the maturity model (figure x).

1. Questionnaire to companies
2. Provide weightings and ratings
3. Combine weightings and ratings
4. Determine maturity ratings
5. Mapping to linguistic terms
6. Final analysis

In this sections we describe the actions and results taken in each step.

Step 1: Send questionnaire to companies

The questionnaire built was sent to dozens of marketing professionals specialized in digital marketing and customer experience in their organizations. Over the two weeks the survey link was open nine receivers responded. The respondents also received a letter attached to the survey which included the outputs and inputs of this research as well as the value the respondents get by answering this questionnaire. The results were sent to the respondents if they asked.

Step 2: Provide weightings and ratings

Based on the information and knowledge each respondents expressed their own evaluation of the rating of each dimension and the importance of it by specifying the weight of the dimension. The rating and weightings are presented in the tables 5 and 6 below expressed both as linguistic terms and as the corresponding triangular fuzzy numbers.

Table 5: Respondent's judgement on ratings and weightings as linguistic terms

	Company1		Company2		Company3		Company4		Company5		Company6		Company7		Company8		Company9	
Sub-dimension	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting
Consent Collection	H	H	H	H	F	VH	VH	VH	H	VH	F	VH	H	VH	H	H	VL	H
Customer 360 view and data orchestration (The use of CDP)	H	VH	F	VH	H	VH	VH	VH	F	H	L	VH	F	VH	H	H	F	VH
Data enrichment with CRM-data	L	H	H	H	F	H	H	VH	L	VH	VL	VH	H	VH	L	H	H	VH
Segmentation	H	H	H	H	F	H	F	VH	H	VH	F	VH	H	F	F	H	F	H
Capturing data with first-party identifiers	F	H	H	H	VH	VH	VH	VH	H	H	F	VH	VH	VH	H	H	H	VH
Customer benefits to share data	F	L	H	F	F	H	F	H	H	L	H	H	VH	F	H	F	F	L
Partnerships	F	H	F	F	F	H	F	H	F	H	H	VH	H	VH	H	H	L	H
Developing a targeting strategy for digital marketing	H	VH	F	H	VH	VH	VH	H	F	F	F	VH	F	VH	VH	H	L	H
Contextual targeting	H	H	F	F	F	H	L	H	H	VH	H	H	H	F	F	H	L	F
Possible to use other targeting methods than cookies (custom audiences)	F	F	H	H	VL	F	F	F	L	F	F	H	L	F	H	H	L	F
Proactive testing	H	VH	F	H	F	VH	H	VH	F	H	F	H	F	VH	H	VH	F	H
Measuring budget	F	H	L	F	F	F	VH	VH	VH	VH	H	VH	F	H	H	VH	F	F
Cookieless modeling methods	H	VH	H	H	VL	H	VH	VH	VH	VH	F	VH	L	H	VH	VH	F	VH
Emphasizing call-to-actions	H	H	F	F	H	H	H	VH	H	F	H	VH	F	H	H	H	F	H
Establishing softer conversions	VH	H	H	F	VH	VH	H	H	H	H	H	H	F	F	H	VH	F	H
Employee expertise	L	F	F	VH	F	VH	F	VH	F	F	F	H	H	H	VH	H	L	H
Server-side-tracking	VH	H	F	H	VL	F	F	VH	L	H	VL	F	F	H	F	H	VL	H
Campaign studies	F	F	F	H	H	VH	VH	VH	F	F	H	H	L	F	VH	VH	H	H
Compatible KPIs	L	F	F	H	H	VH	VH	VH	H	H	F	F	F	H	H	H	H	H
Data clean rooms	VL	L	L	F	VL	F	H	H	L	F	F	F	F	H	F	F	VL	F

Table 6: Respondent's judgement on ratings and weightings as triangular fuzzy numbers

	Company1		Company2		Company3		Company4		Company5		Company6		Company7		Company8		Company9	
Sub-dimension	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting	Fuzzy rating	Fuzzy weighting
Consent Collection	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0,0.1,0.3)	(0.5,0.7,0.9)
Customer 360 view and data orchestration (The use of CDP)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)
Data enrichment with CRM-data	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.7,0.9,1.0)	(0,0.1,0.3)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)
Segmentation	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)
Capturing data with first-party identifiers	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)
Customer benefits to share data	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)
Partnerships	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.5,0.7,0.9)
Developing a targeting strategy for digital marketing	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.5,0.7,0.9)
Contextual targeting	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)
Possible to use other targeting methods than cookies (custom audiences)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0,0.1,0.3)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)
Proactive testing	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)
Measuring budget	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
Cookieless modeling methods	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0,0.1,0.3)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)
Emphasizing call-to-actions	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)
Establishing softer conversions	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)
Employee expertise	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.5,0.7,0.9)
Server-side-tracking	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0,0.1,0.3)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0,0.1,0.3)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0,0.1,0.3)	(0.5,0.7,0.9)
Campaign studies	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Compatible KPIs	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Data clean rooms	(0,0.1,0.3)	(0.1,0.3,0.5)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0,0.1,0.3)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0,0.1,0.3)	(0.3,0.5,0.7)

Worth highlighting from the results is that generally the respondents rate themselves lower than what they weigh the criteria. *First-party data* sub-dimensions received the highest weights, which is different from IAB (2022*b*) results which said that companies were not sufficiently concerned about having enough first-party data in other words they did not weight first-party data that high.

The lowest rated sub-dimension was the employee expertise to implement results, which is also not a surprise considering the results from IAB (2022*b*). However, employee expertise was weighted high, which is inline with the maturity models that emphasize employees like the ones from Rossmann (2018), Hoogveld & Koster (2016), specialists skills is also one of the organizational enablers in Rogers et al. (2021) maturity model. Additionally, custom audiences, data clean rooms, server-side-tracking and enriching first-party data with CRM data received lower ratings. However, first-party data enrichment with CRM-data was the one that had the most deviation in the ratings. One reason for this might that not all of the companies have a comprehensive CRM set up in the first place. This connection would require further investigation.

Most of of the sub-dimensions that were weighted fair were the ones included in the *Develop marketing measurement* dimension. Almost all of the weightings in each sub-dimension were high or very high in average, but data clean rooms and customer benefits to share data received lower weightings. Maybe data clean room is quite new definition so evaluating the performance of it might be difficult. It is somewhat controversial that the respondents do not weight the customer benefits to share with them, but they still have put high weight or very high on consent collection and these two sub-dimension of hand-in-hand, especially when there has been proof of connection between incentives and the willingness to share data with companies (Jai & King 2016, Adobe 2021). Maybe in further development of the model the question measuring data clean room sub-dimension could be altered. The highest weighted sub-dimension was the Customer 360 view and data orchestration, which is mostly enabled by the use of CDP. This dimension was also emphasized in Boufim & Barka (2021) digital maturity model.

Most surprising observation was that almost of the companies weighted the use of other targeting methods than third-party cookies (Cohort targeting) fair, and none weighted it very high. The reason why is this surprising is that cohort targeting methods are the techniques that for example Google is trying to implement to their solutions to replace third-party cookies. As Block (2021) said: cohort targeting has its advantages but it comes along with disadvantages. Maybe the companies were aware of these disadvantages and did not decide to weight it higher. Interesting observation is how the companies answered to questions about cookieless marketing methods and marketing measurement budget. As noted earlier a high third-party cookieless maturity requires a use of cookieless modeling methods like Marketing Mix Modeling, the respondents have agreed with this and weighted cookieless modeling methods high or very high when at the same time they have given themselves a low rating. However, marketing measurement budget sub-dimension has also received Fair weighting. The reason why this observation is highlighted is that methods like Marketing Mix modeling can be expensive therefore can a company even rate themselves high on cookieless maturity modeling if the budget is not set up accordingly. What does it tell about the company is the measurement budget is not weighted high but the cookieless modeling methods are?

Step 3: Combine ratings and weightings

Because there was not multiple respondents from a same organization, aggregation of the responses is not necessary.

Step 4: Determine maturity ratings

By applying the equation 9 the maturity ratings are computed. The results are shown in tables 7.

Table 7: TPCML ratings

	First-party data	Targeting	Develop Marketing measurement
Company1	(1.08, 2.32, 4,55)	(0.84 ,1.72, 3.19)	(1.95, 3.94, 7.04)
Company2	(1.36, 2.76, 5.40)	(0.58, 1.34 ,2.68)	(1.36, 3.24, 6.39)
Company3	(1.50, 2.95, 4.80)	(0.79, 1.56, 2.61)	(1.95, 3.88, 6.61)
Company4	(2.18, 3.86, 5.40)	(0.64, 1.44, 2.69)	(3.58, 6.38, 9.40)
Company5	(1.22, 2.58, 4.70)	(0.62, 1.38, 2.54)	(2.04, 4.16, 7.23)
Company6	(0.95, 2.20, 3.90)	(0.96, 1.92, 3.40)	(1.89, 3.94, 7.29)
Company7	(1.76, 3.32, 5.10)	(0.74, 1.58, 2.75)	(1.38, 3.30, 6.54)
Company8	(1.10, 2.38, 4.90)	(1.00, 1.96, 3.70)	(3.12, 5.72, 9.19)
Company9	(1.09, 2.28, 4.05)	(0.16, 0.72, 1.70)	(1.30, 3.06, 6.30)

The normalization is done with the formula 10 and the required variable a^* is the product of the of the average fuzzy weighting and the highest maturity level rating. The a^* values are presented in table 8

Table 8: a* values

	First-party data	Targeting	Develop Marketing measurement
Company1	5.5	3.7	8.6
Company2	5.7	3.4	8.8
Company3	6.0	3.7	9.1
Company4	6.0	3.7	10.0
Company5	5.5	3.4	8.8
Company6	6.0	4.0	9.1
Company7	5.4	3.4	9.4
Company8	5.7	4.0	9.7
Company9	5.5	3.4	9.4

After we have obtained the *TPCML rating* and the a^* we can calculate the NTPCML rating by using the formula 10. The result are presented in table 9.

Table 9: NTPCML ratings

	First-party data	**Targeting**	**Develop Marketing measurement**
Company1	(0.20, 0.42, 0.83)	(0.23, 0.47, 0.86)	(0.23, 0.46, 0.82)
Company2	(0.24, 0.48, 0.95)	(0.17, 0.39, 0,79)	(0.15, 0.37, 0.73)
Company3	(0.25, 0.49, 0.80)	(0.21, 0.42, 0.71)	(0.21, 0.43, 0.73)
Company4	(0.36, 0.64, 0.90)	(0.18, 0.39, 0.73)	(0.36, 0.64, 0.94)
Company5	(0.22, 0.47, 0.85)	(0.18, 0.41, 0,75)	(0.23, 0.47, 0.82)
Company6	(0.16, 0.37, 0.65)	(0.24, 0.48, 0.85)	(0.21, 0.43, 0.80)
Company7	(0.33, 0.61, 0.94)	(0.22, 0.47, 0.81)	(0.15, 0.35, 0.70)
Company8	(0.19, 0.42, 0.86)	(0.25, 0.49, 0.93)	(0.32, 0.59, 0.95)
Company9	(0.20, 0,41, 0.74)	(0.05, 0.21,0.50)	(0.14, 0.33, 0.67)

Step 5: Mapping the NTPCML rating to linguistic terms

From the results in step 4, each calculated NTPCML can be mapped to a linguistic term in the natural language expression set to represent the level of project maturity. Based on equation 6 the distance between the NTPCML rating and each member of the natural language expression set is calculated. The results are shown in table 10. The maturity level is determined by the the smallest distance of a linguistic term to the NTPCML ratings.

Table 10: Distance between NTPCML ratings and the natural language expression set

Company	**Dimension**	**VL**	**L**	**F**	**H**	**VH**	**min**
	First-party data	0.37	0.21	0.10	0.26	0.41	F
Company1	Targeting	0.41	0.24	0.10	0.22	0.38	F
	Develop marketing measurement	0.39	0.22	0.08	0.24	0.39	F
	First-party data	0.46	0.29	0.15	0.2	0.36	F
Company2	Targeting	0.34	0.18	0.11	0.29	0.44	F
	Develop marketing measurement	0.30	0.14	0.11	0.32	0.47	F
	First-party data	0.39	0.22	0.06	0.22	0.37	F
Company3	Targeting	0.32	0.15	0.07	0.29	0.43	F
	Develop marketing measurement	0.33	0.16	0.07	0.28	0.42	F
	First-party data	0.51	0.34	0.15	0.10	0.25	H
Company4	Targeting	0.31	0.15	0.10	0.3	0.45	F
	Develop marketing measurement	0.53	0.35	0.16	0.10	0.25	H
	First-party data	0.41	0.24	0.10	0.22	0.38	F
Company5	Targeting	0.33	0.16	0.09	0.29	0.44	F
	Develop marketing measurement	0.39	0.22	0.08	0.23	0.38	F
	First-party data	0.27	0.10	0.12	0.34	0.48	L
Company6	Targeting	0.41	0.24	0.09	0.21	0.37	F
	Develop marketing measurement	0.37	0.20	0.09	0.26	0.41	F
	First-party data	0.51	0.34	0.16	0.12	0.27	H
Company7	Targeting	0.38	0.21	0.08	0.24	0.39	F
	Develop marketing measurement	0.28	0.12	0.12	0.34	0.48	L
	First-party data	0.39	0.22	0.12	0.25	0.41	F
Company8	Targeting	0.45	0.28	0.13	0.19	0.35	F
	Develop marketing measurement	0.50	0.33	0.15	0.12	0.28	H
	First-party data	0.33	0.16	0.08	0.28	0.43	F
Company9	Targeting	0.14	0.06	0.25	0.48	0.62	L
	Develop marketing measurement	0.26	0.10	0.14	0.36	0.50	L

Generally most of the companies have a fair maturity level on each of the dimension, None of the companies hold a very high maturity level in any of the dimension. However, some highs and lows can be seen. The reason why many of the companies are in the fair level is the aforementioned fact that almost all the companies put much weight on many of the sub-dimensions but did not rate them correspondingly.

Step 6: Final analysis

Applying the similar logic as earlier the companies final maturity level can be defined, by first taking the average of the each company's final maturity ratings seen in table 10 and then calculating the distance of them to the maturity levels shown in table 1. The final results and the maturity levels where each company land is shown in table 11.

Table 11: Final maturity levels

Company	**Maturity level**
Company1	Defined/Managed
Company2	Defined/Managed
Company3	Defined/Managed
Company4	Managed
Company5	Defined/Managed
Company6	Defined
Company7	Managed
Company8	Managed
Company9	Defined

Companies 1,2,3 and 5 had the same distance to both Defined and Managed levels so to determine their maturity level more specifically further investigation would be required. Companies 6 and 9 "scored" the lowest maturity level and companies 4, 7 and 8 the highest levels. Almost all of the companies that responded represented different industries, so industry level classification cannot be done with the current data. Also, all the companies that answered were headquartered in the EU, so differences between the continents and the underlying privacy regulations cannot be analyzed. Assuming

European companies should have higher maturity level due to the stricter regulations.

7 Conclusion and discussion

In this research the research questions were:

1. How to evaluate companies' readiness and maturity for the deprecation of third-party cookies
2. What is maturity level of companies for the deprecation of third-party cookies

How to evaluate companies' readiness and maturity for the deprecation of third-party cookies?

In the research the answer for the first question was looked from literature review on readiness and maturity. It turned out that several maturity models were already presented in the marketing context most of them focused on B2B marketing or Digital marketing. Additionally, multiple private companies have created their own maturity models that at least scratched the topic of third-party cookies. Based on the literature review and several survey results on this topic a maturity model to measure companies maturity level was built. The model ended up to consist of three dimensions: (1) F*irst-party data*, (2) *Targeting*, and (3) *Develop marketing maturity.* The data for the model was collected via questionnaire. As the answers were based on the subjective assessment of the respondents some impreciseness is involved and to tackle this fuzzy logic was chosen as the approach to quantify and map the answers to linguistic terms.

What is maturity level of companies for the deprecation of third-party cookies?

Companies maturity level in general was fair which means that all the companies landed on the Integrated or Modified maturity level. The dimension where companies scored the highest was first-party data and lowest was develop marketing measurement. This result is not a surprise as the three dimensions in the model can be seen as a hierarchical stepping stones, where the preceding step needs to be well handled before the following step is successfully implemented. In this context it would mean that targeting with complimentary methods to third-party cookies cannot really be done without a good orchestration of first-party data. Furthermore, marketing measurement cannot be developed and implemented successfully if the targeting is not done accordingly based on accordingly orchestrated first-party data. The collected data set did not include a lot of deviation. Nevertheless, there some sub-dimensions that separated the companies from each other. Companies got similar maturity levels in first-party data dimension. On the other hand, the sub-dimension measuring the level of enriching first-party data with CRM data received varying answers. Maybe in future research the model could have a sub-dimensions measuring on what level the companies's CRMs are.

In addition following sub-questions were presented:

1. What are HTTP cookies
2. Why third-party cookies are being removed
3. What are the options for companies after third-party cookies are gone

What are HTTP cookies?

Cookies are a small snippet of code stored on users device. Cookies can be distinguished based on their functionalities and use-cases. Cookies are used to enable some basic functionalities of a website, like shopping cart and login identification. When visiting a website the cookies are considered as first-party, while those set by other domains as a result of loading external resources are considered as third-party cookies. Consequently, if the same third-party resource is present on multiple websites, it enables cross-site tracking: any third-party domain that hosts resources referenced by multiple websites can track users across these sites. This technique allows companies to behaviorally target consumers. Behaviorally targeted ads have increased ROI and because of it the willingness to pay for behaviorally targeted ads is high.

Why third-party cookies are being removed?

Third-party cookies have been the backbone of current digital marketing paradigm and they provide many benefits for publishers, advertisers and consumers. Publishers receive higher revenue, advertisers have increased ROI on their ads and consumers receive advertising that they are more likely to be interested in. However, third-party have major privacy issued related to them and the level of control that consumers have over the data being passed around to different entities is almost nonexistent. Most of the major browsers have already stopped supporting third-party cookies, but Google Chrome has not done yet and they have been postponing the sunset of third-party because they have not been able to develop a functional replacement for the third-party cookies. Google of course is highly motivated to find a replacing technique as good share of Google's revenue is coming through digital marketing which has been dependent on third-party cookies.

Governments have taken actions to protect consumers and their data within the forms of regulations. Most famous ones are the ones in the EU and in the U.S. GDPR and CCPA. In addition, other countries and regions have also implemented their own regulations with the same goal: to protect consumers and especially their PII data. As third-party cookies can be defined as a PII piece of data it will fall under data protection regulations.

What are the options for companies when third-party cookies are gone?

Google has already tried to develop an alternative for third-party cookies. The use of cohort targeting methods is one solution but it has some disadvantages. In addition, techniques like fingerprinting and DNs Cname cloacking that have already been around for while are emerging as a replacement. However, they use the same techniques as third-party cookies so they should not be implemented and from customer perspective are even worse solutions. Furthermore, companies are wanting to find some kind of replacing ID solution, but with them companies need to make sure that their compatible with data protection regulations.

Other solutions that are more consumer friendly are the enhanced use of first-party data and different targeting methods. The removal of third-party cookies is going to launch a renaissance of techniques that are not dependent on third-party cookies like contextual targeting to replace behavioral targeting and Marketing Mix Modeling to replace attribution modeling. In order to successfully implement the replacing targeting methods companies need to

7.1 Discussion

It is not over exaggeration to say that the demise of third-party cookies is going to significantly disrupt the digital marketing ecosystem. This change is mostly initialized by the regulations that have been developed to increase the protection of consumer data. However, according to Thomas (2021) this change is also going to add an insult to an injury when it comes to power distribution in the industry. As targeting is going to require help from companies like Google, Meta and Amazon, companies need to make sure that they are not overly dependent on this kind of companies. To help companies in this the European Commission has stepped with new regulations DSA and DMA. However, due to their novelty their implementation and performance remains to be seen.

If we think about the deprecation of third-party cookies and whether creative destruction or accumulation is more present, one could argue that creative destruction is somewhat non-existent as the digital marketing eco-system in highly dominated by a few parties like Google, Meta and Amazon. However, there are complimentary techniques for third-party cookies as presented earlier, but their relevance in the future can be argued as some of them are not compatible with the current privacy regulations. In addition, digital marketing is not going anywhere and the ad auctions as well as bids are still possible, but the behaviorally targeted ads cannot be bought. As mentioned before, the advertisers willingness to pay for the ad increases when the ad is behaviorally targeted. As a result Beales & Eisenach (2014) argue that the more long tail publishers are the more dependant they are on third-party cookies. Without the revenue from advertising could these smaller publishers vanish or can the new regulations like DMA and DSA, that have the goal to balance the game, be enough to save them?

Further research on this subject could be focused on the factors that lead to a higher maturity level. For example could aforementioned industry and company's location have connection with the maturity level? Especially industries like medical and finance where more delicate customer data is involved, would presumably have higher level of maturity as the studies by (Cahn et al. 2016, Englehardt et al. 2015, Degeling et al. 2018) showed. Could the size of marketing department or budget have positive effect on third-party cookieless maturity? Other interesting point of analysis would be the amount of digital marketing done in-house. All of the companies that answered to this questionnaire had bought some kind of marketing consulting services from an agency. Would a more in-house marketing department have a higher maturity or vice versa? Or could the agency from which a company has purchased digital marketing services be the better entity to answer the questionnaire as they might be more aware of the day-to-day operations or campaigns that are ran? The results from IAB (2022*b*) survey showed that brands were least prepared for the loss of third-party cookies and the agencies came in second after the Ad tech/data companies. This current maturity model was designed specifically for brands who act as the advertisers, but it could be altered to be targeted to agencies and publishers as well.

In this research we have only talked about digital marketing, so it would be interesting to see how the "traditional" brands, who have built brand offline and not online, would perform compared to the more digitally oriented brands. This kind of analysis would be especially interesting in the develop marketing measurement dimension, as the more traditional measurement methods are coming to back to marketers toolbox . Traditional might have already the expertise to measure and implement results from campaign studies. Or could it be that the more agile digital marketers that have well tested and targeted campaigns outperform the traditional methods?

In addition as Johnson et al. (2020) and Jai & King (2016) showed, demographic factors have an affect on how consumers react to privacy questions and targeted advertisements. At the end of the day, the decisions that companies make are made by people, so if decision makers are privacy fundamentalists, as Jai & King (2016) defined, is the company taking the actions required for higher third-party cookieless maturity more seriously?

In the questionnaire, a question about the companies awareness of how third-party cookies are used in their marketing was added. Even though many of the companies assessed that they were either aware or very aware they still did not give themselves very high ratings. As the subject is still quite new and its effects as well as the complimentary technologies are still in a phase of development, maybe the companies had falsely thought that they were more aware of the use of third-party cookies than they actually are. To use this model in the future one could organize a workshop or some kind of session where the subjects and terms are elaborated for the questionnaire respondents. Maybe even short wiki or a glossary could be attached to the questionnaire.

The goal of this research was to developed a tool to quickly measure company's third-party cookie maturity level. This research does not provide answers on how companies can increase their maturity level or specific instructions and recommendations what are the actions companies should take. The maturity model developed is a framework that optimizes the process and tools that could offer companies desired solutions. Maturity model by itself is not going to increase anyone's maturity, but it brings tidiness to strategic plans and fosters continuous improvement. Only time will tell what are the actual impact that the demise of third-party cookies is going to have on digital marketing. Even though 100 percent clarity about the effects are not seen in the horizon, it is clear that mature companies are going to have smoother sailing in the quickly changing digital marketing eco-system.

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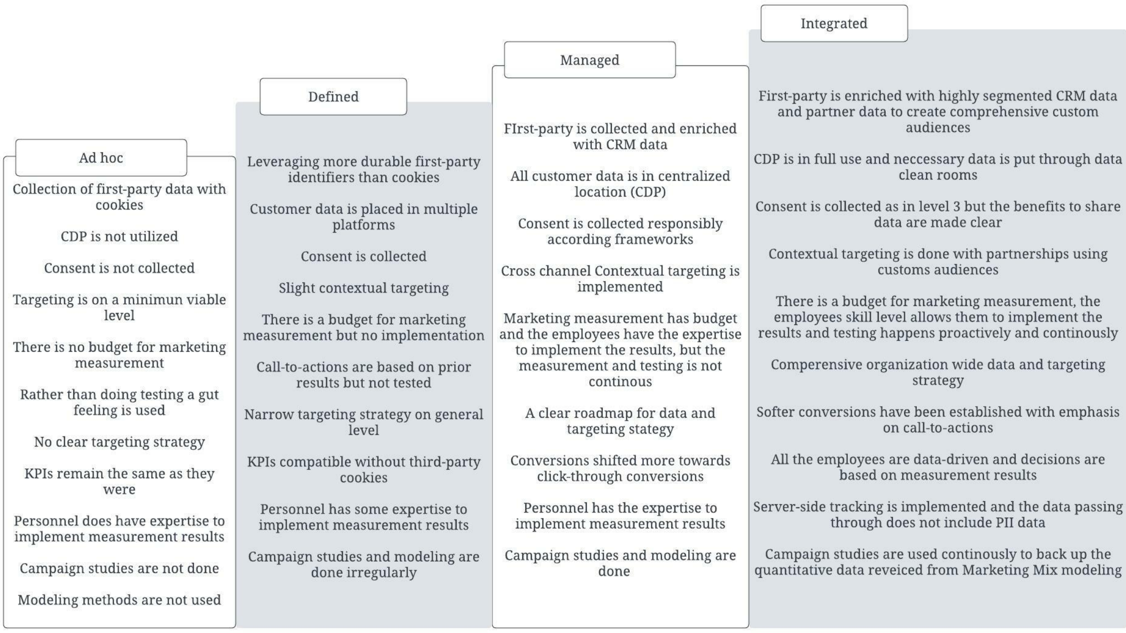
Appendix

Appendix A

Maturity levels for third-party cookieless maturity



Appendix B

Questionnaire

Companies' maturity in the world without third-party cookies

(untitled)

1.
Company name *

2.
Company size by employees (Globally) *

- 1-4
- 5-9
- 10-49
- 50-249
- 250-499
- 500+

3.
Which country is your company's headquarters currently located? *

4.
Are you aware how third-party cookies are currently used in your marketing operations? *

	1	2	3	4	5	
Not aware at all	○	○	○	○	○	**Very aware**

First party tracking

5.
How well are you currently collecting consent from customers to share data? *

We do not collect consent	We collect consent fairly	We have a consent opt-in pop-up window	We collect consent compatibly with GDPR and have implemented Consent Management Platfrom (CMP)	We collect consent and store it in data privacy center
○	○	○	○	○

6.
How would you weight the importance of collecting consent? *

	1	2	3	4	5	
Very Low	○	○	○	○	○	**Very High**

7.
On what level are your own data capturing capabilities? *

We do not capture or store our own customer data	We capture customer data on some level but do not store it	We capture customer data and store it in a Customer Data Platform (CDP)	We capture customer data and store it compatibly with regulations	We capture data and have 360 view on the customer
○	○	○	○	○

8.
How would value the importance of own data capturing capabilities and the use of CDP? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

9.
On what level is your marketing data enriched with CRM data? *

	1	2	3	4	5	
Very poor	○	○	○	○	○	**Very good**

10.
How important you think it is to enrich your own marketing data with CRM data after 3rd-party cookies are gone? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

11.
How comprehensive are your customer segments? *

	1	2	3	4	5	
Not comprehensive at all	○	○	○	○	○	**Very compresensive**

12.
How important you think it is to have comprehensive customer segments? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

13.
How well have you captured more durable identifiers like emails and phone numbers? *

	1	2	3	4	5	
Not well at all	○	○	○	○	○	**Very well**

14.
How much would you value more durable identifiers? *

	1	2	3	4	5	
Not valuable at all	○	○	○	○	○	**Very valuable**

15.
Have you presented to your clients/customers comprehensively and clearly the benefits of sharing data with you? *

	1	2	3	4	5	
Not well at all	○	○	○	○	○	**Very comprehensively and clearly**

16.
How much weight would you put on incentives for sharing data with you? (for example loyalty programs or whitepapers) *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

Targeting

17.

How good and comprehensive are your partnerships with media and other data providers? *

	1	2	3	4	5	
We do not have partnerships at all	○	○	○	○	○	**We have multiple and strategic partnerships and we utilize partner provided second party data**

18.

How much weight would you put on data partnerships? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

19.

Have you established a targeting strategy for digital marketing? *

We do not have a targeting strategy	We have thought of establishing a targeting strategy	We have a targeting strategy	Our targeting strategy is formalized, communicated and approved	Targeting strategy is integrated as part of the marketing strategy
○	○	○	○	○

20.
How would you value a targeting strategy for digital marketing? *

	1	2	3	4	5	
Not valuable at all	○	○	○	○	○	**Very valuable**

21.
How is your utilization of contextual targeting? *

	1	2	3	4	5	
Very poor	○	○	○	○	○	**Very Good**

22.
How important you think the utilization of contextual targeting is after the third-party cookies are gone? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

23.
Are you utilizing cohort marketing methods like custom audiences for targeting? *

	1	2	3	4	5	
We do not use cohort marketing methods	○	○	○	○	○	**Our targeting strategy relies on cohort marketing**

24.
How much weight would you put on cohort marketing methods? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

Marketing measurement

25.
What kind of testing culture your marketing organization has? *

	1	2	3	4	5	
We do not test at all	○	○	○	○	○	**We do comprehensive proactive testing**

26.
How would you weigh proactive testing culture? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

27.
What kind of marketing measuring budget do you have? *

	1	2	3	4	5	
We do not have marketing measurement budget	○	○	○	○	○	**We have a solid budget specifically for marketing measurement**

28.
How important is marketing measurement budget to you? *

	1	2	3	4	5	
We do not need one	○	○	○	○	○	**It is very important to have specifically budgeted marketing measurement**

29.
Do you use cookieless modeling methods to measure our performance (for example: Marketing mix modeling (ROMI-Modeling))? *

	1	2	3	4	5	
We do not use any type modeling methods	○	○	○	○	○	**We utilize different modeling methods continuously**

30.
How important for you it is to continuously measure your marketing performance? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

31.
How would you rate the call-to-actions in your ads? *

	1	2	3	4	5	
Very poor	○	○	○	○	○	**Very good**

32.
How much weight would you put on call-to-actions in your ads? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very Important**

33.
Have you established "softer" conversions alongside with the "harder" ones? *

We do not have any conversions	We only have view-through based conversions	We have click-based conversions	We have both view-through based conversions and hard click-based conversions	We have reviewed our conversions and added more softer click-based conversions alongside with our harder conversions
○	○	○	○	○

34.
How important you think it is to add more softer click-based conversions? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

35.
How would you rate your employee expertise to implement the results from different measurements? *

	1	2	3	4	5	
Very poor	○	○	○	○	○	**Very good**

36.
How much weight would you put on employee expertise to implement results? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

37.
How well have you set up server-side-tracking? *

We have not set up server-sider-tracking	We thought of setting up server-side-tracking	We are currently setting up server-side-tracking	We have moved away from legacy tools like Universal Google Analytics and set-up server-side-tracking	We have server-side-tracking up and running for a while already
○	○	○	○	○

38.
How much weight would you put on establishing server-side-tracking? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

39.
How do you conduct campaign studies? *

	1	2	3	4	5	
We do not conduct them	○	○	○	○	○	**We conduct them continuosly**

40.
How much weight would you put on campaign studies? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

41.
How compatible are your Key Performance Indicators (KPIs) with the world without 3rd-party cookies? *

	1	2	3	4	5	
Very poor	○	○	○	○	○	**Very compatible**

42.
How much weight would you put for setting up compatible KPIs? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

43.
How well have you utilized data clean rooms? *

	1	2	3	4	5	
Very poorly	○	○	○	○	○	**Very well**

44.
In your opinion, how valuable you think data clean rooms are? *

	1	2	3	4	5	
Not important at all	○	○	○	○	○	**Very important**

45.
Do you wish to receive the information on your maturity level to your email? *

- ○ Yes
- ○ No

46.
Please provide your email