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Velkommen til den enogtredivte udgave af 'Nyhedsbrevet om Forbrugeradfærd'. I dette nummer af Nyhedsbrevet bringes to interessante artikler.

I den første artikel med titlen 'Digital customer experience: An emerging theme in customer service excellence' undersøger Lars Grønholdt, hvorledes forskellige dimensioner af 'digital customer experience' (DCE) påvirker 'business performance'.

I den anden artikel beskæftiger Jens Koed Madsen sig med 'The Psychology of Micro-Targeted Election Campaigns', og herunder hvorledes politiske kampagner i stigende grad anvender detaljerede vælgerdata, endda helt ned på individniveau. Udover artiklen udgiver Jens Koed Madsen til efteråret en bog om emnet, som også er omtalt i artiklen.

Digital customer experience: An emerging theme in customer service excellence[1]

Lars Grønholdt, Copenhagen Business School

Abstract

Purpose: The purpose of the paper is to examine how essential dimensions of digital customer experience (DCE) drive business performance.
Methodology/approach: An empirical study is conducted to investigate the relationships between seven DCE dimensions and business performance. The conceptual model is operationalized by a structural equation model, and the model is estimated and tested by using the partial least squares method. A survey of 756 companies in Denmark forms the empirical basis for the study.
Findings: The findings provide evidence that the seven DCE dimensions influence business performance. All seven DCE dimensions are essential in producing total customer experience, market performance, and financial performance.
Research limitations: The study is limited to the seven identified DCE dimensions in Danish companies.
Practical implications: The study has clear implications in terms of identifying and measuring the importance of essential DCE dimensions which influence business performance. Interesting differences appear between the seven indexes for DCE dimensions. The results can help companies to understand DCE and develop DCE strategies.
Originality/value: The paper provides insight into DCE and how DCE works.
Key words: Digital customer experience, market performance, financial performance
Paper type: Research paper

Introduction

In recent years, creating and managing digital customer experiences seems to be a key area for many companies on "leveraging digital advancement for the growth of organizations and achieving sustained commercial success" (Bones and Hammersly, 2017, p. 128). Digital advancements has attracted great attention from marketing academics and practitioners (Borowski, 2015; Cliff, 2018; Lywood et al., 2009; Palmer, 2008, 2010; Verhoef et al., 2009). Sharma and Chaubey (2014, p. 18) claim that "the customer experience has emerged as the single most important aspect in achieving success for companies across all industries".

The literature on customer experience is growing fast, and the debate among scholars and practitioners is very lively.

[1] Paper submission to the 22nd QMOD-ICQSS Conference 2019.

However, "the greatest challenge for customer experience management lies in the difficulty of measuring the concept, which is specific to a situational and emotional context" (Palmer, 2008). Moreover, Brakes et al. (2009, p. 52) state that "research has largely ignored the exact nature and dimensional structure of brand experiences". The present study addresses these challenges and examines how digital customer experience (DCE) can be measured and how different dimensions of DCE influence business performance.

The present study is initiated and conducted as a research project between Copenhagen Business School, Denmark (CBS, www.cbs.dk) and House of Loyalty, Denmark (www.sj@stigjorgensen.as) with the support of several Danish data, insights and consulting companies.

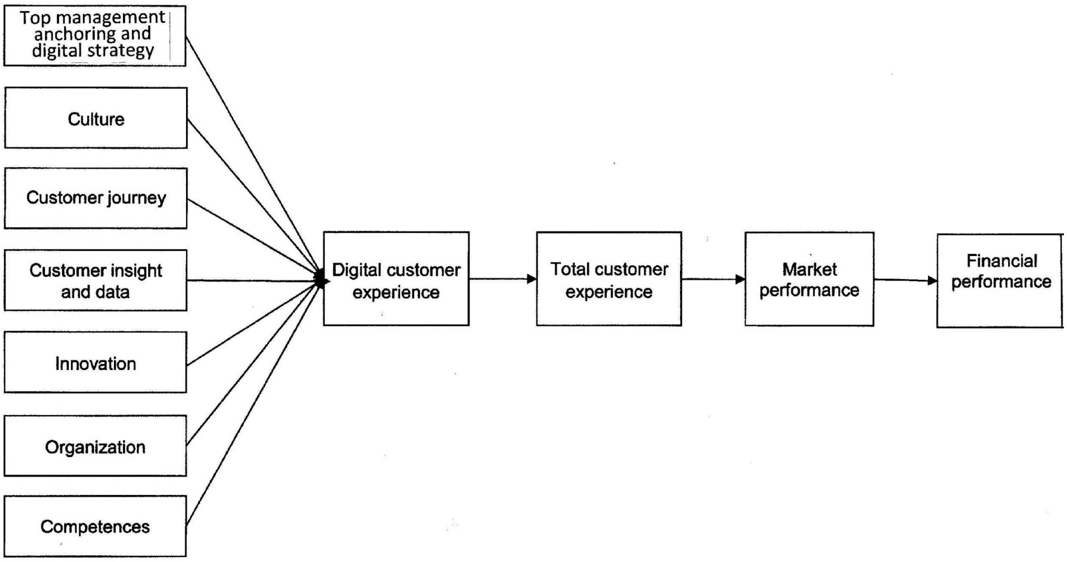
The structure of the paper is as follows. Firstly, the essential dimensions of DCE are identified and discussed. Secondly, a conceptual model of the relationships between the DCE dimensions and business performance is developed. Thirdly, the research methodology is presented: measures development, data collection, and the modelling approach. Fourthly, data analyses results are presented and discussed. And fifthly, concluding remarks are provided in the closing section of the paper.

Linking DCE to business performance

Based on literature reviews (i.a., McColl-Kennedy et al., 2015; Gupta, 2018), case studies from the literature (i.a., Frow and Payne, 2007; Gupta, 2018), and practical work with DCE an initial frame of reference of DCE was developed. This outlined a set of characteristics of DCE describing relevant areas of actions in the company: Top management anchoring and digital strategy, culture, customer journey, customer insight and data, innovation, organization, and competences (see the conceptual model in Figure 1).

For each of the areas, survey questions are developed based on Shaw (2017) and practical work with DCE surveys. An empirical study (see next section) suggests that it would be appropriate to organize the initial DCE characteristics in seven DCE dimensions. Hence, analyzing survey responses from 484 companies using factor analysis (see next section) gave new insight into how to structure and describe the DCE concept with good sense. The seven dimensions (factors) are shown on the left-hand side of the conceptual model (see Figure 1).

Figure 1. The conceptual DCE model



The conceptual model in Figure 1 shows the links between DCE dimensions, DCE, total customer experience, market performance, and subsequently financial performance.

Methodology

Measurements development

The conceptual model's eleven variables are viewed as latent variables, which are measured by 2-6 measurement variables or items (measured by survey questions). The seven dimensions of DCE have been deduced from literature studies and confirmative and explorative factor analysis. The model structure is at this moment supported by data which in turn makes good sense to the model (face validity).

The survey questions which have been used to measure the seven DCE dimensions are partly inspired by Shaw's work with customer experience in general (Shaw, 2017), partly based on practical work with measuring DCE and customer experience, and partly developed for the this study explicitly.

Measurements of market performance and financial performance have been done by using established scales from academic literature: Desphandé et al. (1993), Homburg and Pflesser (2000), Moorman and Rust (1999), and Zhou et al. (2009).

All questions are generic which means they are formulated in such a flexible manner that they can be used across companies and industries. At this moment, the estimation results can be compared across companies and industries which allow using the results in benchmarking studies. It is a distinct advantage for this model and the attached measurement system. The developed questionnaire consists of 44 questions regarding DCE and total customer experience, and 10 questions regarding the two business performance variables.

The respondent answers all questions on a 7-point scale. Questions regarding DCE and total customer experience concern the respondent's company. The respondent is asked to mark from 'strongly disagree' to 'strongly agree' on the statements provided. Answers to questions regarding market and financial performance are to be scaled from 'much worse' to 'much better' compared to competitors.

Data collection

In 2019 we conducted an online survey across several industry and service sectors in Denmark to capture a broad variety of market settings. Our unit of analysis is the company, and the data contains 484 useable interviews with company managers in Denmark. Most of the managers held top management positions such as marketing manager, director (responsible for marketing and sales activities within the company) or member of the executive.

A structural equation modelling approach

The conceptual model in Figure 1 is operationalized as a structural equation model which links each latent variable with the corresponding measurement variables (the measurement model) and links the latent variables through causal relationships (the structural model) symbolized by the arrows in Figure 1.

The structural equation model is estimated and tested by using partial least squares (PLS) due to this method's advantages: PLS is distribution-free and it is robust (against skew distributions for measurement variables and multicollinearity) (Cassell et al., 1999; Chin, 1998; Fornell and Bookstein, 1982; Hulland, 1999; Tenenhaus et al., 2005). Furthermore, PLS is a powerful method for predictive applications, as PLS aims at explaining variances (Fornell and Cha, 1994).

We follow the recommended two-stage analytical procedure for the PLS approach to structural equation modeling (Fornell and Larcker, 1981; Hair et al., 2012; Hulland, 1999): Firstly, the measurement model was evaluated, and then the structural model including estimation and testing of the model. In both stages, the software SmartPLS (Ringle et al., 2019) was used.

Data analysis results

Measurement model evaluation

Initially, several analyses were carried out to assess the measurement variables (items) and the latent variables in the model.

The reliability and validity of the scales were examined. Firstly, item reliability was measured by Cronbachs' alfa factor loading. We found from the SmartPLS output that the lowest loading was 0.72, indicating that item reliability of the scale measures was acceptable. It is recomended, that Cronbach's alpha of an item is 0.7 or more (Carmines and Zeller, 1979; Hulland, 1999).

Secondly, composite reliability (internal consistency) was assessed using the composite reliability coefficient recommended by PLS researchers, and an acceptable level is said to be 0.7 or higher (Baumgartner and Homburg, 1996; Chin, 1998; Fornell and Larcker, 1981; Hulland, 1999). We found that all composite reliability coefficients were higher than 0.85 and exceeded the recommended threshold. Also, we used the average variance extracted (AVE), which should be higher than 0.5 (Chin, 1998; Fornell and Cha, 1994; Fornell and Larcker, 1981). The AVE for all latent variables clearly exceeds this condition, since the lowest reported AVE value is 0.60, demonstrating composite reliability for all latent variables also in that way. Thirdly, discriminant validity is present if the square root of AVE of a latent variable is more extensive than its correlations with the other latent variables (Chin, 1998; Fornell and Larcker, 1981; Hulland, 1999). The criterion is met for all latent variables, which indicates that the latent variables in the model are distinct. Thus, with acceptable reliability and validity assessments, our measures were considered to be appropriate for subsequent estimation and test of the causal model.

Estimation of the DCE model

The results of the PLS estimation of the model are shown in Figure 2. The estimates of the impacts (path coefficients) between the latent variables in the model are displayed by the arrows, and DCE indexes, total customer experience and performance indexes are shown inside the variables in the figure. As expected, all estimated impacts are positive. The estimated indexes for each variable - from 0 (poor) to 100 (excellent) - indicate the average level among the participating companies in the study. The impact scores are effects of a one-point increase in a variables' index on the following variable.

To test the significance of the path coefficients the bootstrap resampling procedure is applied, and all relationships in the model are statistically significant (all t values > 17.6, all p values < 0.001).

By estimating the model an explanatory power of $R^2 = 0.61$ for financial performance is achieved, i.e., the model explains 61 % of the variation in financial performance. For market performance and total customer experience, the explanatory power is respectively $R^2 = 0.53$ and $R^2 = 0.56$. These R^2 values indicate a good overall model fit.

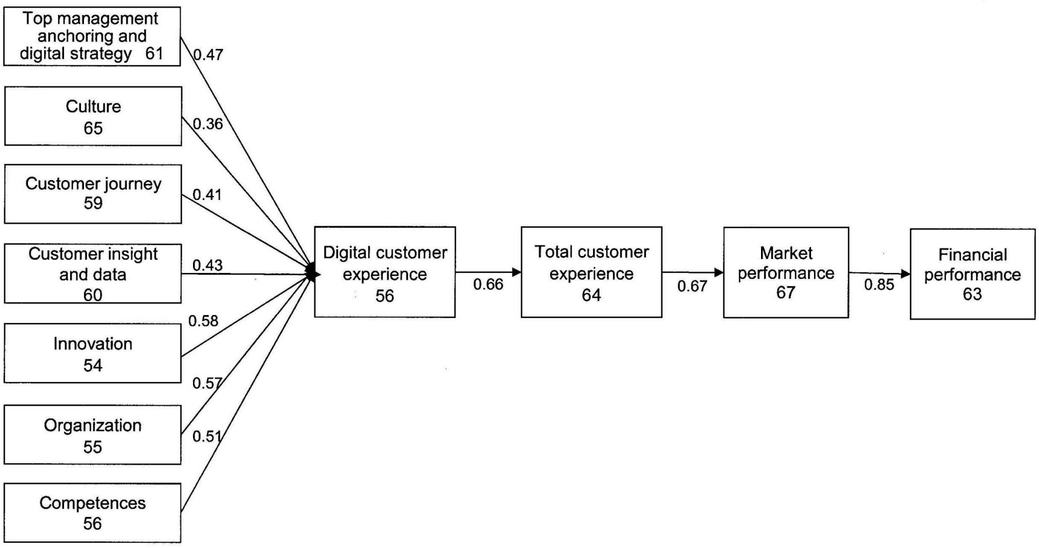
In conclusion, the quality of the model is good with strong explanatory power. Thus, there is a high certainty and precision in the results and conclusions to be drawn from the study.

Results and discussion

Clear evidence of the relationship between DCE and financial performance

The model estimation results show that there is a strong relationship between DCE and financial performance as illustrated in Figure 2. All DCE dimensions have a positive influence on digital customer experience, which in turn has a positive and significant influence on both market performance and financial performance. Moreover, as expected, market performance influences financial performance.

Figure 2. The estimated DCE model



Differences between the DCE dimensions

Interesting differences can be observed between the seven indexes for DCE dimensions. The three lowest indexes is for innovation, organization, and competences. It is noticeable that these three DCE dimensions have the largest impact on DCE. Against this background, companies in general should generally focus on improving innovation, organization and competences with a view to increasing DCE, total customer experience, market performance, and finally financial performance.

Conclusion

The present paper has investigated DCE and its influence on business performance. The developed DCE model provides a comprehensive means of covering important dimensions of DCE as well as a better understanding of these dimensions' link to business performance. The seven DCE dimensions make good sense to Danish managers. The model has been empirically validated, and all relationships in the model are statistically significant indicating a solid model. The quality of the model is good with strong explanatory power, and the conclusions drawn from the study reflect high confidence and precision.

The data analyses presented in the paper provide evidence that all seven DCE dimensions influence business performance. The presented model is limited to seven identified DCE dimensions. It is possible that an alternative structure of the dimensions or new dimensions – cf. the introductory remarks on the growing literature and debate on DCE – may provide even more convincing conclusions. The study is the second of a yearly DCE index that measures DCE based on the same survey set-up and modeling approach as presented in this paper. Some survey questions are added in 2019 to reveal actual DCE themes and trends.

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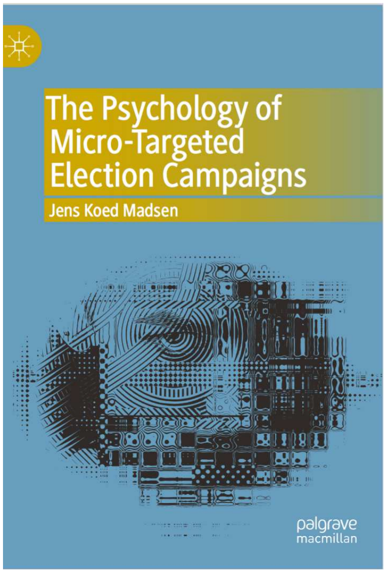
The Psychology of Micro-Targeted Election Campaigns

Jens Koed Madsen (University of Oxford)

Introduction

Politics, persuasion, and the pursuit of power are endless sources of wonder to people who live in deliberative democracies. Aside from the people *with* actual power, there is a great interest for people in the opposition who plan usurp the reigns of control as well as all the political operatives, pundits, and lobbyists that naturally congregate around the scene. In deliberate democracies politicians of course gain power by winning elections. Recently, election campaigns have become better structured and planned by professional campaign managers. In an attempt to go beyond running the campaigns on gut feeling, instinct, or heavy reliance on past strategies, campaigners' increasingly make use of data to run campaigns more effectively. As a consequence, this has become a field of academic and popular-scientific interest (Nielsen, 2012; Issenberg, 2012, Bimber, 2014; Hersch, 2015).

This important development is thoroughly discussed in the upcoming book, *The Psychology of Micro-Targeted Election Campaigns* (Madsen, in press).



Data can be used to generate statistics at the level of cities, states, and nations (e.g. the demographic spread in a province, past voter turnout, or number of polling stations for a district). This kind of population-level data is useful to get rough approximation of an area and the people who live there generally. This can be useful to help the campaign figure out, at a general level, which political issues to focus on in an election, or if an area is contestable in constituency-based democracies (as opposed to proportional representation).

Population-level data is certainly helpful, as they can inform the campaign of the characteristics of an area, provide general polling on the popularity of specific issues, and inform on the viability of a specific candidate. However, the campaign may want to go beyond societal-level descriptions and approximate what a *particular* person will vote in an upcoming election. After all, some persuasive efforts and policy proposals may work well with a subset of the public, but may be counterproductive with another. This is due to the fact that the reception of a persuasive attempt or the evaluation of a policy proposal is coloured by the listener's subjective prior beliefs, by how they perceive the credibility of the speaker, and possibly by individual psychological traits. At heart, an electorate is heterogeneous in their beliefs, desires, and preferences.

Due to heterogeneity, campaigners may therefore seek personalised information about a specific voter. This may include the person's digital footprint or consumption habits, which might be able to inform on demographic traits (income, gender, sexuality, etc.), personal beliefs (political preferences, perceived candidate credibility, supposed ideological position, etc.), and the person's psychometrics (personality profile, biases, etc.). Armed with this information, Campaigners can sharpen their models of people, test basic assumptions about belief and behaviour change, and generate progressively specific messages designed to fit a specific segment of the electorate. The process of generating gradually personalised and segmented models of people and using this for persuasion efforts is known as *micro-target campaigning*. If the campaign's model assumptions are good and if they have relevant data about the electorate, this type of campaigning should, in theory, give a strategic and tactical advantage compared with population-level or stochastic campaigns (see Madsen & Pilditch, 2018).

Cambridge Analytica

Unquestionably, Cambridge Analytica (defunct since 2018) is the most famous case of a political micro-targeted campaign in recent times. Cambridge Analytica was a London-based company that used data-driven, psychologically informed micro-targeted models to develop and optimise political strategies and campaigns. According to reports, they used an array of databases to generate increasingly accurate personalised persuasion efforts. They provided analytical assistance for Republican candidates in 2014 (Issenberg, 2015; Vogel & Parti, 2015; Sellers, 2015) and 2016 (Tett, 2017; Confessore & Hakim, 2017) as well as work for the pro-leave campaign in the 2016 Brexit referendum (Doward & Gibbs, 2017; Cadwalladr, 2017, 2018).

To develop their strategies, they allegedly used demographic and consumer data, to estimate specific people's political leanings and preferences, the likelihood that this specific voter would turn out on Election Day, if the voter live in a competitive area, and other salient metrics. This kind of segmentation helps to identify people who are likely to be swing voters in competitive areas, which tells the campaign *who* to target.

Going beyond *whom* to target, data can also be used to segment people along lines of expected policy preferences. For example if a person buys organic products, they may be more likely to care about environmental issues. If the campaign has access to multiple data points for each voter concerning the digital footprint (e.g. what kind of hashtags did the person use, who does the person follow on social media, what does the person buy, etc.), the model can guesstimate their policy preferences. This informs the campaign on *what* to say to the voter. Identifying the target subsets of the electorate and learning about their policy preferences is naturally beneficial to running effective campaigns.

In addition to using data to identify whom to target and what to target them with**,** Cambridge Analytica reportedly generated personality profiles for voters to further segment the electorate by harvesting data from 87 million people via Facebook (Kang & Frenkel, 2018; Hern, 2018). Psychometric profiles enable additional segmentation along personality lines, which may inform the style of persuasion (e.g. for one issue, they may develop different persuasion messages for highly conscientious and highly extraverted voters). Through continuous message A/B-testing and development, the campaign can learn *how* to talk about an issue for *that* voter.

People disagree on the impact of data analytics. Some argue data has become a powerful tool for predicting people and influencing behaviour (e.g. Monbiot, 2017) while others point to the fact that data has failed to predict specific elections (Lohr & Singer, 2016). For Cambridge Analytica, some argue it impacted election campaigns significantly while others argue the methods are ineffective and that predicting people in general is very difficult (Trump, 2018; Chen & Potenza, 2018; Nyhan, 2018)

Understanding micro-targeted campaigns in principle

While it is historically interesting to speculate whether Cambridge Analytica influenced the 2016 election, it is meaningless for considering whether micro-targeted campaigns are generally able to provide a strategic or tactical advantage. By their very nature, elections come and go. The causal predictors and the strength of their influence on a given election can be difficult, if not impossible, to determine.

Models are only as good as the foundational assumptions upon which their house is built and as the data that inform that construction. Campaigners may have inaccurate assumptions about the electorate, data that informs the models may be corrupted or poorly tabulated, and outside and unexpected events may invalidate the predictive power of the models. In addition, opposing campaigns may use better models, or the candidate may be terrible (in which case, no amount of data can salvage an electoral train wreck).

Due to the noise of individual outcomes, it would be foolish to proselytise on the effects (or lack thereof) of data-driven micro-targeted campaigns. Comparatively, it is more informative to consider what data can and cannot do. Some may believe data is unable to predict anything, both at population- and individual-level. If this is true, micro-targeted campaigns would be wasteful and entirely irrelevant (as would any social science that makes use of data). More realistically, data can tell us something about people and their societies. The upcoming book, *The Psychology of Micro-Targeted Election Campaigns,* explores how campaigners can use psychologically informed, data-driven models to improve the success of their persuasive attempts.

Theories of persuasion have undergone significant transformations throughout history. In ancient Athens, philosophers, sophists, and rhetoricians explored when and why people changed their minds. They developed qualitative theories via philosophical discussion, observation of speeches, and practical discourse. In the 20th century, theories of persuasion were tested empirically. The Elaboration-Likelihood Model (Petty & Cacioppo, 1986), cognitive heuristics (Kahneman, 2011), and the principles of persuasion (Cialdini, 2007) employ psychological experimental methods and explore quantitatively observable outcomes. Measuring persuasive efforts and success quantitatively enabled researchers to test the validity of theories and assumptions.

In the past decades, researchers have made advances in formal, mathematical models that quantitatively predict (rather than merely describe) how people may change their beliefs or adapt their behaviours when faced with incentives, persuasive messages, or argumentation (see e.g. Hahn & Oaksford, 2006; 2007). Amongst these, we find so-called Bayesian models that take point of departure in people's *subjective, personal* view of the world (Oaksford & Chater, 2007) and of people's *perceived* credibility of the speaker (Bovens & Hartman, 2003; Hahn et al.; 2009; Harris et al., 2015). Quantitative, predictive models allow researchers to test and explain relevant cognitive functions in increasingly precise and scientific ways.

As we learn more about people, we get a better understanding why they change their beliefs and act in specific ways. That is, what are the functions that underpin belief revision, and what are the main factors for behaviour? Understanding these functions is paramount to running a successful campaign, as winning the hearts and minds of the electorate and getting them to turn out on Election Day is the primary campaign focus. The campaign may build a thorough understanding of the target electorate – what makes them vote, what are their political preferences, and so forth?

Using insights from fields like social and cognitive psychology and behavioural economics, campaigners can design persuasive attempts that speak to core functions that are relevant to persuading the electorate to vote for the preferred candidate. Continuous collection of relevant data can be used to implement quantitative models and test the effectiveness of persuasive efforts, as they are being developed and employed. If the campaign has access to relevant data for the electorate and the outcome of their attempts, they can test and sharpen their basic assumptions and measure their efforts as they proceed with the campaign.

Aside from generating individual voter profiles that inform what to talk about and how to talk about it, data can be used to identify the most relevant voters for a given election. In proportional democracies, every voter is relevant to persuade, as each person influences the election as much as the next person. As such, no person is more relevant than another. However, some countries, such as the UK and the USA, are constituency-based democracies where areas (boroughs or states) determine the winner. While some areas tend to be safe for a party (e.g. California is likely to vote for the Democratic candidate next election), contested areas tend to determine the outcome (this is not always the case as a candidate may breeze through an election by winning not only traditionally contested areas, but also areas that are marginal oppositional strongholds).[2] In a constituency-based system, voters become increasingly relevant if they live in a contested area *and* if they can be persuaded to vote for your preferred candidate (e.g. for both parties, campaign finances would be wasted in California, as the Republicans are unlikely to win the state and the Democrats can presume to have won it without doing much campaigning).

Quantifiable and formal models can capture the individual differences within the public. Data-driven, psychologically informed micro-targeted campaigns make use of psychological insights to develop messages that fit their desired, specific audience, and they make use of data to fit their models and measure the success of their efforts. This enables campaigns to effectively figure out whom to target (e.g. finding swing voters who are amenable to the candidate), learn how best to persuade them (by testing their persuasive attempts through trial and error for that voter segment before contacting the actual audience), and model their predicted impact on the election.

Book overview

The Psychology of Micro-Targeted Campaigns explores how campaigners can use psychological insights to create realistic models of the electorate to predict how they will respond to attempts to change their beliefs or behaviours. In order to do so effectively, campaigns segment the electorate strategically along psychological, demographic, and electoral lines to identify the most relevant voters and figure out how best to persuade *that* part of the electorate. The book explores the general principles that underpin how this can be done – specific uses will change from election to election and country to country, but the underlying intentions and principles for building such models remain constant.

Chapters 1-4 explore how models of persuasion have gone from qualitative and descriptive theories to quantitative and predictive models of persuasion. Specifically, the chapters explore how researchers can capture people's subjective beliefs and model how they will integrate new information from sources they perceive as more or less credible. Having presented these models, chapters 5-7 discuss how data can be used to quantify the importance of a voter for a given election, how the electorate can be segmented along

[2] The 1936 presidential election in the USA yielded the largest difference in electoral outcome. Franklin D. Roosevelt gained 60.8% of the vote, which gave him an impressive 98.49% of the Electoral College votes (523-8). Not a good day for opposing candidate, Alf Landon.

personalised lines, and how micro-targeted campaigns can be built. In addition to this, chapter 8 considers the influence of negative campaigning.

Chapter 1-8 thus focus on micro-targeted campaigns that target individual voters by uncovering who can be persuaded to change their beliefs. In doing so, campaign managers use data to segment the electorate into distinct psychological and demographic categories to be targeted. Voters can be categorised along personal lines such as their subjective beliefs, their perception of the credibility of candidates or other sources of information, or personal psychological traits such as personality. These measures can help the campaign divide the electorate into distinct categories, which can subsequently be used to test specific persuasion efforts to determine which arguments work well for which segments of the electorate.

Fundamentally, the models described in chapters 1-8 represent each voter in isolation from social engagements. Individual-oriented use of psychological profiling can be described as *analytic* micro-targeted campaigns. This identification and segmentation of individuals seem to be the usual model for micro-targeted campaigns. It is highly useful to identify the most relevant voters, segment the electorate, and to develop messages that specifically fit each electoral subset. However, this segmentation process models people in isolation. As we know, information dissemination increasingly takes place in bottom-up environments such as social media where citizens become active influencers and disseminators of news and opinions. When systems are characterised by interactions between people, have high degree of heterogeneity, and unfolds over time, it becomes difficult for analytic models to predict how persuasive efforts will live beyond the initial interaction. That is, whether the campaign message ends up going viral (and thus reaches well beyond the intended subset of voters).

Going beyond analytic micro-targeted campaigns, chapter 9-10 explore how campaign managers can improve their models based on knowledge about the social position of a voter as well as their understanding of how information can spread on social media. Given agency to interact with other voters, a voter who, alone, might not influence the election much may be a considerable asset if they have an extended social network. For example, social influences may be tremendously useful assets in election campaigns when seeking to motivate the political base. Consider the actions of the singer Taylor Swift as an example of this. Toward the mid-term Election of 2018, she posted an Instagram message where she identified as a Democrat and urged her fans to register to vote. According to reports, roughly 65.000 new voters registered to vote within 24 hours of her initial Instagram post (Snapes, 2018). When models include the social position of the individual voter and how individual and collective behavioural patterns can emerge as a product of interactions, they are described as *dynamic*.

Aside from campaign benefits, interactions between voters can also pose a challenge for campaigns that run on analytic profiling. Agency also means that voters can share the campaign material. Hypothetically, a data-driven campaign may identify a subset of the population that responds particularly well to fear-based adverts. Through analytic segmentation, the campaign may develop incredibly effective, fear-based adverts for *that* segment. However, this kind of campaign material, while effective for the *intended* subset of the electorate, may be incredibly counter-productive for the rest (who may think fear-based campaigns are crass, dangerous, or bigoted). Given the fact that people can post on social media, a voter might post (earnestly) the fear-based advert, which in turn may be incredibly damning for the campaign. In this way, highly targeted persuasive attempts designed for a very specific subset may backfire when the campaign is spread (by the voter) on social media.

Dynamic micro-targeted models enable campaigns to predict how persuasive attempts and information can travel through networks such as social media. This can be used to minimise the risk by capturing the agency of voters. In addition, dynamic models can provide a blueprint for the optimal use of the networks and the voters who reside and act within them.

In all, the book discusses how campaign managers can use analytic or dynamic data-driven, psychologically informed models to profile individual voters and their social position in order to improve the success of persuasive attempts.

Concluding remarks

Of course, political micro-targeting can be harmful when it is used to manipulate the electorate, when providing unfair political advantages, or when used to deliberatively disseminate misinformation. However, while it can be used malevolently, the techniques can also be used positively for social goods. For example, an in-depth understanding of causes for discrimination generates better interventions to combat this; similarly, psychologically valid models of behaviour informed by personalised data may make public health campaigns more effective. As with all methods, micro-targeting can be used malevolently and positively. However, unless we understand the methods, we cannot generate appropriate rules and regulations for campaigns and fair data use.

As such, the intention of *The Psychology of Micro-Targeted Campaigns* is not to vilify the methods. Rather, the book presents what they fundamentally are. This requires a presentation of the methods in principle and a discussion of how they function. Further, possibly fuelled by the case of the company Cambridge Analytica, discussions of the use of personal data in politics tend to veer from one hyperbole to another: 'they control us all' versus 'humans are too complex to possibly model'. The truth is naturally in between. If the models are accurate and informed by relevant data, they give a significant advantage. However, they cannot deterministically elect any candidate. Therefore, the book provides a clearer idea of what these models can and cannot do.

Personalised data relevant to political persuasion becomes ever more ubiquitous and accessible. We live in an information age where companies and governments collect huge swathes of data for each citizen. As persuasion models become increasingly precise, such data can be used to build formidable models that represent critical functions such as belief revision, social network influence, and likelihood of voting.

Deliberative democracies live and die by the quality of information. While the models are never deterministic or all-powerful, we have to ensure regulatory frameworks for politics that minimise unfair advantages, reduce the impact of campaign funding, and ensure productive rules for elections and public discourse. On a societal scale, it is crucial to understand how information can diffuse and be spread through social networks, how people integrate that information within their pre-existing beliefs, and how campaigns can use and abuse psychological profiling to conduct acts of persuasion as effectively as possible. If we want to understand their impact on our democracies, we cannot rely on hyperbolic representations. Instead, we have to realise what micro-targeted campaigns built on psychological insights can and cannot do to influence our citizens, manage our elections, and shape our societies. *The Psychology of Micro-Targeted Campaigns* provides the conceptual framework for this discussion.

Biography

Jens Koed Madsen is a Senior Research Assistant at the School of Geography and the Environment at the University of Oxford. He is also a fellow at the Oxford Martin School and the Institute of New Economic Thinking as well as a research associate at St. Catherine's College, University of Oxford.

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