Summary
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Digital technologies have dramatically changed the way citizens are informed about political and societal issues. Citizens can consume news anytime, anywhere, and from a wide range of sources on a growing number of devices (de Vreese & Neijens, 2016). Citizens, especially younger adults, are increasingly and predominantly using online and social media to get informed about the world around them. With the rise of digital technologies and platforms, news consumption is becoming increasingly individualized and personalized (Pariser, 2011; Stroud, 2011). News consumption in the digital society strongly differs from a “one size fits all” context, with a single homogeneous news supply for all citizens. In today’s news media landscape, every experience is unique. Citizens are often directed to news that is sent, shared, or liked by their friends, family, and acquaintances. Besides, algorithms increasingly tailor search results or sort news based on digital traces of personal data (e.g., a citizen’s past behavior, sociodemographics, social ties, or inferred similarity to other citizens).

The rise of digital technologies has important consequences for the way citizens are informed. Some scholars are optimistic and believe that digital technologies contribute to the quality of democracy. Digital technologies, for example, enable citizens to deal with the information overload and find more interesting content. Other scholars fear that digital technologies have negative implications for political life. Citizens increasingly consume news that algorithms select for them, potentially resulting in filter bubbles, polarization, and fragmentation (Pariser, 2011; Sunstein, 2007). This dissertation contributes to this important debate in the field of political communication.

It is of crucial importance to understand which news is consumed by whom, and how (in which context). The overall research question of this dissertation is: “To what extent do content features, consumer features, and context features of news media interact in affecting how citizens consume news and, ultimately, affect interest in politics and engagement with political news?”. To date, existing studies are usually limited to one or two of those components, while it is ultimately the combination and interaction of all three components to study news consumption in the digital society. This dissertation integrated these three features into one framework: the CCC-model. It highlights the importance of addressing: (1) content features (i.e., what?, such as news topics), (2) consumer features (i.e., who?, such as sociodemographics, political interest), and especially (3) context features (i.e., how?, the role
of social ties and algorithms as opposed to a “one size fits all” context). Integrating content, consumer, and context features into one theoretical framework enables the development of a new understanding of examining and thinking about news consumption in the digital society.

The first part of this dissertation examines to what extent content features, consumer features, and context features shape patterns of news consumption. The first study examines television news consumption. By combining audience-meter data with survey data and subtitle data, this study investigates which political topics are covered by various formats and genres in public service television; and, more importantly, how this can be connected to important predictors of news use, namely political interest and political ideology. In the next study, the dissertation moves from television to online news consumption, or, in other words, it moves from a “one size fits all” context to a setting with unique user experiences. By passively tracking online news consumers, this study examines the way news consumers combine news websites, search engines, and social media, as well as a variety of news topics (e.g., politics, entertainment), while navigating online. With more and more news sources to choose from, citizens have become more selective in their news consumption choices. This dissertation demonstrates that political preferences (e.g., political interest, political ideology) play a key role in understanding patterns of news consumption. Politically interested citizens consume more political news, whereas those who prefer non-political news opt for more entertaining options. This gap does become wider in the digital society.

The second part of this dissertation examines the consequences of digital technologies and platforms for citizens’ interest in politics and engagement with political news. By conducting an experimental study among adolescents, the third study addresses the effects of sharing and discussing political news in the context of instant messaging apps. The results demonstrate that digital platforms, such as instant messaging apps, serve as a resource for engaging younger citizens with political and societal issues. Social ties (e.g., friends, family, and acquaintances) are the driving force behind the effects. Social ties not only shape news consumption, but also positively affect the way citizens respond to discussing political news. Relying on two-wave panel survey data, the final study of this dissertation provides insights into the reciprocal effects between news consumption and political preferences (e.g., political interest, news media trust). Data for this study was collected just before and during the COVID-19 pandemic. Although reciprocal effects between news use and political interest were evident predominantly with traditional news outlets, the results indicate that digital platforms can also positively affect political life. Even though the effects are small, they contribute significantly to citizens’ interest in politics and engagement with political news.
Taken together, this dissertation builds on established theories and the empirical possibilities enabled by large data sets to understand news consumption in the digital society. Some of the findings justify the pessimistic view of earlier work. That is, citizens highly interested in politics are more likely to consume political news compared to citizens that are less interested in politics, and that due to the context in which news consumption happens, those effects might be accelerated. This dissertation also shows that digital technologies and platforms contribute to the quality of political life. The findings reveal that citizens not only have access to a great variety of outlets that provide information about political and societal issues, but many citizens also make use of these outlets. Digital platforms, such as instant messaging apps, may serve as a source for engaging younger citizens with political and societal issues. Theoretically, this dissertation highlights that features affecting patterns of news consumption (i.e., content features, consumer features, and especially context features) can no longer be studied in isolation, but need to be considered in relation to other features. This dissertation reframes research questions in debates such as polarization, news avoidance, selective and incidental exposure. Future research should definitely ask more specific questions about the role of social networks and algorithms in today’s news media landscape. For instance, how do algorithms infer what citizens seem to be interested in? What factor is most influential? For which citizens? What are the effects? Such questions are important because they determine whether digital technologies and platforms undermine or improve political life.
Taken together, this dissertation builds on established theories and the empirical possibilities enabled by large data sets to understand news consumption in the digital society. Some of the findings justify the pessimistic view of earlier work. That is, citizens highly interested in politics are more likely to consume political news compared to citizens that are less interested in politics, and that due to the context in which news consumption happens, those effects might be accelerated. This dissertation also shows that digital technologies and platforms contribute to the quality of political life. The findings reveal that citizens not only have access to a great variety of outlets that provide information about political and societal issues, but many citizens also make use of these outlets. Digital platforms, such as instant messaging apps, may serve as a source for engaging younger citizens with political and societal issues. Theoretically, this dissertation highlights that features affecting patterns of news consumption (i.e., content features, consumer features, and especially context features) can no longer be studied in isolation, but need to be considered in relation to other features. This dissertation reframes research questions in debates such as polarization, news avoidance, selective and incidental exposure. Future research should definitely ask more specific questions about the role of social networks and algorithms in today’s news media landscape. For instance, how do algorithms infer what citizens seem to be interested in? What factors are most influential? For which citizens? What are the effects? Such questions are important because they determine whether digital technologies and platforms undermine or improve political life.
Samenvatting

Digitale technologieën hebben nieuwsgebruik drastisch veranderd. Tegenwoordig is het nieuws op elk moment van de dag en waar je ook bent toegankelijk (de Vreese & Neijens, 2016). Er is een enorme diversiteit aan nieuwsbronnen en deze zijn via een groot aantal apparaten bereikbaar. Burgers, en met name jongeren, consumeren het nieuws in toenemende mate via online en sociale media. Door de groei van digitale technologieën en platformen is nieuwsgebruik persoonlijker en individueel geworden (Pariser, 2011; Stroud, 2011). In een digitale samenleving is het nieuwsaanbod niet langer voor iedereen hetzelfde, zoals het lezen van de krant of het kijken van het achtuurjournaal. Via online en sociale media worden burgers steeds vaker via vrienden, familie, of kennissen op de hoogte gebracht van het laatste nieuws. Daarnaast consumeert men in toenemende mate nieuws dat door algoritmes wordt geselecteerd. Algoritmes passen zoekresultaten aan en rangschikken het nieuws op basis van digitale sporen en persoonlijke gegevens (zoals zoekgedrag, demografische kenmerken, sociale connecties, of gedrag van burgers met vergelijkbare kenmerken).

De toename van digitale technologieën heeft belangrijke gevolgen voor de manier waarop burgers worden geïnformeerd. Sommige wetenschappers zijn optimistisch en geloven dat digitale technologieën het makkelijker voor burgers om te gaan met een grote stroom informatie en interessantere berichten te vinden. Andere wetenschappers waarschuwen dat digitale technologieën negatieve gevolgen kunnen hebben voor een democratie. Met de komst van informatietechnologieën, en daarmee de belangrijke rol van sociale connecties en algoritmes, is de kans groot dat burgers met meer politieke interesse worden gewezen op politiek nieuws. Dit kan mogelijk leiden tot zogenoemde filterbubbels, polarisatie en fragmentatie (Pariser, 2011; Sunstein, 2007). Dit proefschrift draagt bij aan dit belangrijke debat in politieke communicatie en journalistiek.

Het is van groot belang om te onderzoeken welk nieuws door wie wordt geconsumeerd, en met name hoe dat gebeurt (in welke context). In dit proefschrift wordt onderzocht in welke mate kenmerken van de inhoud van nieuws (content; wat?, zoals nieuwsonderwerpen), kenmerken van de nieuwsconsument (consument; wie?, zoals demografische kenmerken, politieke interesse) en voornamelijk kenmerken van de omgeving waarin nieuws wordt
geconsumeerd (context; *hoe*, zoals de rol van sociale connecties en algoritmes) interacteren en nieuwsgebruik bepalen. Eeerder onderzoek heeft zich gericht op slechts één of twee van deze componenten. Het is juist de combinatie en de interactie van alle drie de componenten die noodzakelijk is om nieuwsgebruik in een digitale samenleving te begrijpen. Dit proefschrift combineert deze drie componenten in één theoretisch raamwerk: het CCC-model. Het integreren van deze drie kenmerken maakt het mogelijk om nieuwsgebruik in een digitale samenleving beter te begrijpen, te analyseren en te verklaren.

In het eerste gedeelte van dit proefschrift wordt de rol van content, consument en context kenmerken onderzocht. In de eerste studie wordt televisie als nieuwsbron onderzocht. Data vanuit kijkcijferkastjes wordt gecombineerd met vragenlijstonderzoek en ondertiteling van televisieprogramma's. Dit onderzoek bekijkt welke politieke onderwerpen aan bod komen in een grotere variatie aan nieuws- en actualiteitenprogramma's van de publieke omroep en wat de rol is van politieke interesse en politieke ideologie in het bepalen van nieuwsgebruik. In het volgende onderzoek verschuift het focus van het proefschrift van televisie naar de online context. Door nieuwsgebruikers online te volgen door middel van een browser plug-in, wordt onderzocht hoe nieuwsgebruikers diverse online nieuwsbronnen, zoals nieuwswebsites, zoekmachines en sociale media, en nieuwsunderwerpen (bijv. politiek en entertainment) combineren als ze online navigeren. Door het toegenomen aanbod van nieuwsbronnen worden burgers selectiever in hun nieuwsconsumptie. Dit proefschrift toont aan dat individuele voorkeuren zoals politieke interesse en ideologie een cruciale rol spelen in nieuwsgebruik. Burgers met meer politieke interesse consumeren meer politiek nieuws, en burgers die minder geïnteresseerd zijn in de politiek geven de voorkeur aan nieuws dat meer gericht is op entertainment. De scheidslijn lijkt groter te worden in een digitale samenleving.

Het tweede deel van het proefschrift onderzoekt de effecten van digitale technologieën. Door middel van experimenteel onderzoek met jongvolwassenen, richt de derde studie zich op de effecten van het delen en bespreken van politiek nieuws in de context van *instant messaging*. De resultaten tonen aan dat online platformen, zoals WhatsApp, een belangrijk medium kunnen zijn om jongvolwassenen te betrekken bij politieke en maatschappelijke onderwerpen. Sociale connecties (bijv. vrienden, familie of kennissen) bepalen niet alleen welk nieuws burgers online tegenkomen, maar beïnvloeden op een positieve manier ook hoe ze daar op reageren. Het laatste onderzoek van dit proefschrift richt zich op de wederzijdse effecten tussen nieuwsgebruik en politieke uitkomsten (bijv. politieke interesse, vertrouwen in nieuwsmedia). Deze studie richt zich op longitudinaal vragenlijstonderzoek. De data voor dit onderzoek werd verzameld net voor en tijdens de COVID-19 pandemie. Wederzijdse effecten worden met name gevonden voor traditionele nieuwsmedia, desondanks toont het
laatste onderzoek aan dat er een wederzijds effect bestaat tussen politieke interesse en het gebruik van bijvoorbeeld mobiele nieuwsapplicaties. De resultaten tonen aan dat online platformen een positieve impact kunnen hebben op de samenleving. Ondanks dat de effecten klein zijn, dragen ze bij aan de interesse en interactie van burgers met politiek nieuws.


Appendices
Chapter 2

Content features

We explore four types of television programs, namely (1) news, (2) current affairs, (3) opinion, and (4) satire.

News

First, we turn our attention to news programs (e.g., news broadcasts). The topics discussed in such programs vary from Politics and Sports to Government and Weather forecasting (see Figure 20a). Next, we created a topic-network. In total, the topic-network consists of 20,041 nodes (i.e., topics) and 955,621 edges (i.e., topics that co-occurred in the same chunk). To obtain a better understanding of the topics we use a community detection approach. Networks are often characterized by clustering, which is hard to judge by eye. There are many existing community detection approaches (Luke, 2015). As we employ undirected and weighted networks, we rely on the Louvain community detection algorithm in igraph (Csardi & Nepusz, 2006). Modularity is fairly acceptable (.71), suggesting that the Louvain algorithm has done a good job at detecting subgroup structure in our topic-network. “Modularity is a measure of the structure of the network, specifically the extent to which nodes exhibit clustering where there is greater density within the clusters and less density between them” (Luke, 2015, p. 115). The membership function reveals that 1,129 different subgroups have been identified. Examining the six largest clusters, we can see a clear divide of topics (see Table 10): (1) Foreign relations, (2) Politics, (3) Environment, (4) Business, (5) Sports, and (6) Transportation.

In order to get a better and deeper understanding of television news consumption, we re-run the Louvain community detection algorithm on the clusters covering political content. The results are presented in Table 10.
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**Table 10: Largest topic clusters and examples: News**

1. **Foreign relations**
   - Law
   - Politics of the Middle East
   - Human rights
   - Immigration
   - Active citizenship
   - Politics of the Balkans
   - Politics of Russia & Turkey
   - Organized crime groups
   - Politics of Cuba
   - Politics of South-Africa
   - Interpol, Political corruption, Nuclear disarmament
   - Al-Qaeda, Arab-Israeli conflict, Islamic State
   - Dési Bouterse, LGBT rights, Child abuse, Slavery
   - Refugees, Immigration law, Antisemitism
   - Protests, Movements for civil rights, Demonstrations
   - Srebrenica, Serbia, Bosnia and Herzegovina
   - Alexei Navalny, Erdoğan, Presidency of Russia
   - Sicilian Mafia, Giovanni Falcone, Hells Angels
   - Fidel Castro, Cuban Revolution, Presidents of Cuba
   - Netherlands-South Africa relations, Port Elizabeth

2. **Politics**
   - Political parties
   - Politics of the U.S.
   - Royalty
   - Local government
   - European Union
   - Military
   - Economy
   - Politics of Kenya
   - Politics of Great Britain
   - Politics of Austria
   - Politics of Belgium
   - Politics of the Dutch Carribean
   - Binnenhof, Ank Bijleveld, GroenLinks
   - The Republican Party, Barack Obama, Bill Clinton
   - European royalty, Queen Máxima of the Netherlands
   - Ahmed Aboutaleb, Municipal council
   - European Parliament, Frans Timmermans
   - Royal Netherlands Army, Vlissingen, Military forces
   - Ministers of Economic Affairs of the Netherlands
   - Nairobi, Raila Odinga, Presidents of Kenya
   - Sinn Féin, Politics of Northern Ireland, Brexit
   - Vienna, Sebastian Kurz, The Austrian Parliament
   - Vlaams Belang politicians, Filip Dewinter
   - Politics of Sint Maarten, William Marlin

3. **Environment**

4. **Business**

5. **Sports**

6. **Transportation**
**Politics**

As shown in Table 12, the six largest clusters cover: (1) *Health*, (2) *Politics*, (3) *Law*, (4) *Foreign relations*, (5) *Sports*, and (6) *Environment*.

**Table 11: Largest topic clusters and examples: Current affairs**

| 1. Health                          | Disease outbreaks, Cancer treatments, Cigarettes |
| 2. Politics                        | Mayors of Amsterdam, Overijssel politicians, Onno Hoes |
| - Local government                 | 50PLUS, Mona Keijzer, Khadija Arib |
| - Political parties                | Willem-Alexander of the Netherlands, Soestdijk Palace |
| - Military                         | Royal Netherlands Navy, Marines, Military forces |
| - Economy                          | Ministers of Economic Affairs of the Netherlands |
| - Organized crime groups           | Hells Angels, Satudarah, Criminal subcultures |
| - Politics of Austria              | Vienna, Sebastian Kurz, The Austrian Parliament |
| 3. Law                             | Law enforcement, Civil rights, Child labor, LGBT rights |
| 4. Foreign relations               | European Commission, Brexit, Frans Timmermans |
| - European Union                   | LGBT rights, Hate crime, Child abuse |
| - Human rights                     | Law enforcement, Offender profiling, International law |
| - Law                              | Extremism, Cold War, Military strategy |
| - Politics of Italy                | Matteo Salvini, MEPs for Italy, Mussolini family |
| - Conflict                         | Homelessness, Affordable housing, Social movements |
| - Social issues                    | Angela Merkel, Bundestag, Government of Berlin |
| - Politics of Germany              | Government of Spain, Barcelona, Government of Catalonia |
| - Politics of Spain                | Nairobi, Raila Odinga, Presidents of Kenya |
| - Politics of Kenya                | Gerard Piqué, FIFA, Hockey |
| 5. Sports                          | Climate change, Greenhouse gas, Energy transition |
| 6. Environment                     |                                    |

**Opinion**

Next, we turn our attention to television programs covering opinion (e.g., talk shows, documentaries)—representing 10,765 nodes and 219,979 edges. The top topics can be found in Figure 21a. Again, we identified multiple clusters within this topic-network (*n* = 1,790; modularity = .71). As shown in Table 12, the six largest clusters cover: (1) *Entertainment*, (2) *Politics*, (3) *Communication*, (4) *Human interest*, (5) *Sports*, and (6) *Culture*. 
As shown in Table 12, the six largest clusters cover: (1) Politics, (2) Communication, (3) Law, (4) Foreign relations, (5) Sports, and (6) Culture. The top topics can be found in Figure 21a. Again, we identified multiple clusters within this topic-network (consists of 1,905 nodes and 15,823 edges. We identified multiple clusters within this topic-network (consists of 1,905 nodes and 15,823 edges).

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Finally, we focus on satire. We present the top topics in Figure 21b. The network of satire consists of 1,905 nodes and 15,823 edges. We identified multiple clusters within this topic-network (n = 534; modularity = .79). The six largest clusters are: (1) Foreign relations, (2) Human interest, (3) Politics, (4) Environment, (5) National holidays, and (6) Culture (see Table 13).
Table 13: Largest topic clusters and examples: Satire

<table>
<thead>
<tr>
<th>1. Foreign relations</th>
<th>Freedom of education, Freedom of speech, Liberty</th>
</tr>
</thead>
<tbody>
<tr>
<td>· Human rights</td>
<td></td>
</tr>
<tr>
<td>· Democracy</td>
<td>Voting, Petitions, Elections</td>
</tr>
<tr>
<td>· Politics of Germany</td>
<td>Bundestag, Germany and the European Union, Angela Merkel</td>
</tr>
<tr>
<td>· Diplomacy</td>
<td>Stef Blok, Ministers of Foreign Affairs of the Netherlands</td>
</tr>
<tr>
<td>· European Union</td>
<td>European Parliament, Frans Timmermans, European Commission</td>
</tr>
<tr>
<td>· Politics of China</td>
<td>Mao Zedong, Xi Jinping, Communist Party of China</td>
</tr>
<tr>
<td>· Aviation</td>
<td>Amsterdam Airport Schiphol, Lelystad Airport</td>
</tr>
<tr>
<td>2. Human interest</td>
<td>Fast food, Home, Self-care, Wine, Weight loss</td>
</tr>
<tr>
<td>3. Politics</td>
<td></td>
</tr>
<tr>
<td>· Parliament</td>
<td>Ministries, Cabinet of the Netherlands</td>
</tr>
<tr>
<td>· Political parties</td>
<td>GroenLinks, Liberal parties, Republican parties</td>
</tr>
<tr>
<td>· Royalty</td>
<td>House of Orange-Nassau, Prince Bernhard of Orange-Nassau</td>
</tr>
<tr>
<td>4. Environment</td>
<td>Renewable energy, Fossil fuels, Biomass</td>
</tr>
<tr>
<td>5. National holidays</td>
<td>Public holidays, Christmas, Easter, Zwarte Piet</td>
</tr>
<tr>
<td>6. Culture</td>
<td>Cinema, Arts, Music, Postmodernism, Amusement parks</td>
</tr>
</tbody>
</table>

Exemplary database structure (MySQL)

Consumer features – individual-level (N = 3,672)

<table>
<thead>
<tr>
<th>ID</th>
<th>HHID</th>
<th>Gender</th>
<th>Age</th>
<th>· · ·</th>
<th>Political interest</th>
<th>Political ideology</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>M</td>
<td>42</td>
<td>·</td>
<td>3</td>
<td>Left</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>F</td>
<td>39</td>
<td>·</td>
<td>2</td>
<td>Left</td>
</tr>
<tr>
<td>·</td>
<td>·</td>
<td>·</td>
<td>·</td>
<td>·</td>
<td>·</td>
<td>·</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>M</td>
<td>8</td>
<td>·</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

Consumer features – household-level (N = 1,761)

<table>
<thead>
<tr>
<th>HHID</th>
<th>Province</th>
<th>Age of head of the household</th>
<th>· · ·</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Friesland</td>
<td>42</td>
<td>·</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>North Holland</td>
<td>82</td>
<td>·</td>
<td>2</td>
</tr>
<tr>
<td>·</td>
<td>·</td>
<td>·</td>
<td>·</td>
<td>·</td>
</tr>
<tr>
<td>4</td>
<td>Groningen</td>
<td>38</td>
<td>·</td>
<td>5</td>
</tr>
</tbody>
</table>
### Table 13: Largest topic clusters and examples: Satire

1. Foreign relations
   - Human rights
     - Freedom of education, Freedom of speech, Liberty
   - Democracy
     - Voting, Petitions, Elections
   - Politics of Germany
     - Bundestag, Germany and the European Union, Angela Merkel
   - Diplomacy
     - Stef Blok, Minister of Foreign Affairs of the Netherlands
   - European Union
     - European Parliament, Frans Timmermans, European Commission
   - Politics of China
     - Mao Zedong, Xi Jinping, Communist Party of China
   - Aviation
     - Amsterdam Airport Schiphol, Lelystad Airport

2. Human interest
   - Fast food, Home, Self-care, Wine, Weight loss

3. Politics
   - Parliament
     - Ministries, Cabinet of the Netherlands
   - Political parties
     - GroenLinks, Liberal parties, Republican parties
   - Royalty
     - House of Orange-Nassau, Prince Bernhard of Orange-Nassau

4. Environment
   - Renewable energy, Fossil fuels, Biomass

5. National holidays
   - Public holidays, Christmas, Easter, Zwarte Piet

6. Culture
   - Cinema, Arts, Music, Postmodernism, Amusement parks

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**Television viewership (N = 2,420,142)**

<table>
<thead>
<tr>
<th>Date</th>
<th>HHID</th>
<th>Channel</th>
<th>Start</th>
<th>Length</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>03/01/2018</td>
<td>1</td>
<td>NPO1</td>
<td>18:58</td>
<td>59:03</td>
<td>1, 2, 3, 4</td>
</tr>
<tr>
<td>03/01/2018</td>
<td>1</td>
<td>NPO1</td>
<td>19:57</td>
<td>10:04</td>
<td>1, 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>03/01/2018</td>
<td>1</td>
<td>NPO2</td>
<td>21:32</td>
<td>23:01</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>04/01/2018</td>
<td>2</td>
<td>NPO1</td>
<td>17:09</td>
<td>29:01</td>
<td>1, 2</td>
</tr>
</tbody>
</table>

**Context features – programs (N = 21,480)**

<table>
<thead>
<tr>
<th>Date</th>
<th>Channel</th>
<th>Program</th>
<th>Program ID</th>
<th>Start</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>03/01/2018</td>
<td>NPO1</td>
<td>EenVandaag</td>
<td>1V03</td>
<td>19:00</td>
<td>19:55</td>
</tr>
<tr>
<td>03/01/2018</td>
<td>NPO1</td>
<td>NOS Journaal</td>
<td>NOS03</td>
<td>20:00</td>
<td>20:11</td>
</tr>
<tr>
<td>03/01/2018</td>
<td>NPO2</td>
<td>Nieuwsuur</td>
<td>N03</td>
<td>21:30</td>
<td>22:22</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>04/01/2018</td>
<td>NPO1</td>
<td>Tijd voor Max</td>
<td>TVM04</td>
<td>17:10</td>
<td>17:55</td>
</tr>
</tbody>
</table>

**Content features – subtitles (N = 63,718)**

<table>
<thead>
<tr>
<th>Program ID</th>
<th>Subtitles</th>
</tr>
</thead>
<tbody>
<tr>
<td>1V03</td>
<td>“We staan hier in station Vijzelgracht (…)”</td>
</tr>
<tr>
<td>NOS03</td>
<td>“Die ontvingen daarvoor zelfs de Nobelprijs voor de Vrede (…)”</td>
</tr>
<tr>
<td>N03</td>
<td>“Cryptomunten zijn een hype (…)”</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>TVM04</td>
<td>“Rusland probeert invloed te krijgen in Europa (…)”</td>
</tr>
</tbody>
</table>
Table 14 presents a list of all domain names included in our sample.

**Table 14: List of white-listed websites**

<table>
<thead>
<tr>
<th>Type of website</th>
<th>Domain names</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabloids</td>
<td><a href="http://www.telegraaf.nl">www.telegraaf.nl</a> (also telegraaf.tcdn.nl, m.telegraaf.nl, krant.telegraaf.nl, content.tmgvideo.nl, vaarkrant.telegraaf.nl, beta.telegraaf.nl), <a href="http://www.ad.nl">www.ad.nl</a> (also video.ad.nl, krant.ad.nl, social.ad.nl, nieuws.ad.nl) (12)</td>
</tr>
<tr>
<td>Broadsheets</td>
<td><a href="http://www.volkskrant.nl">www.volkskrant.nl</a> (also krant.volkskrant.nl, ins.volkskrant.nl, verhalen.volkskrant.nl, inclusief.volkskrant.nl), <a href="http://www.nrc.nl">www.nrc.nl</a> (also retro.nrc.nl, digitaal.nrc.nl), <a href="http://www.trouw.nl">www.trouw.nl</a> (also krant.trouw.nl, exclusief.trouw.nl, beta.trouw.nl) (12)</td>
</tr>
<tr>
<td>Online-only outlets</td>
<td><a href="http://www.nu.nl">www.nu.nl</a> (also media.nu.nl, secure.nu.nl, link.nu.nl), <a href="http://www.nieuws.nl">www.nieuws.nl</a> (5)</td>
</tr>
<tr>
<td>Social media</td>
<td><a href="http://www.facebook.com">www.facebook.com</a> (also 1.facebook.com), <a href="http://www.twitter.com">www.twitter.com</a> (3)</td>
</tr>
</tbody>
</table>
Performance measures

In our study, we employed the Passive-Aggressive (PA) learning algorithm, which is known to perform well in various text classification tasks (Crammer et al., 2006), including Dutch-language news items (see e.g., Burscher et al., 2015).

Before training each classifier, we converted the text to a bag-of-words model and used this as the input for the model. Different pre-processing steps have been used resulting in three different text categories. (1) The first category comprises the original text of the news item. (2) Next, we removed Dutch stop words such as articles (e.g., the, a and an), personal pronouns (e.g., I, me and he), coordinating conjunctions (e.g., for, but and so), and prepositions (e.g., in, towards and before). We retrieved the list of stop words from the Python NLTK package (see Bird & Loper, 2016). (3) Finally, after removing stop words, we examined the lead (i.e., first 75 words) of each news item, as facts are generally presented in descending order of importance (Pöttker, 2003).

We split the dataset into a training set (80 percent; N = 2,963) and a test set (20 percent; N=738), and used the former for training and the latter for testing. Additionally, we tested various combinations of hyperparameters to find the ultimate combination, for example determining: how to convert a collection of text documents to a matrix of token counts (CountVectorizer), whether to transform a count matrix to a normalized tf or tf-idf representation (TfidfTransformer), and the maximum number of passes over the training data (i.e., epochs). Table 15 presents the ultimate combination of hyperparameters to tune the classifier.

Table 15: Performance measures and hyperparameters for the PA algorithm

<table>
<thead>
<tr>
<th></th>
<th>All words</th>
<th>Stop words</th>
<th>Lead</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Performance measures</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td>.82</td>
<td>.82</td>
<td>.81</td>
</tr>
<tr>
<td>Precision</td>
<td>.82</td>
<td>.82</td>
<td>.81</td>
</tr>
<tr>
<td>Recall</td>
<td>.83</td>
<td>.82</td>
<td>.82</td>
</tr>
<tr>
<td><strong>Hyperparameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CountVectorizer()</td>
<td>1,1</td>
<td>1,1</td>
<td>1,1</td>
</tr>
<tr>
<td>TfidfTransformer()</td>
<td>True</td>
<td>True</td>
<td>True</td>
</tr>
<tr>
<td>Optimization Iteration</td>
<td>15.0</td>
<td>5.0</td>
<td>10.0</td>
</tr>
<tr>
<td>Hinge-Loss function</td>
<td>L2-loss</td>
<td>L2-loss</td>
<td>L2-loss</td>
</tr>
</tbody>
</table>

As the PA algorithm examining all words computes a high accuracy for every topic (see Table 16), we used this algorithm to classify news items in our sample (see Vermeer, 2018).
Table 16: Performance measures for the PA algorithm per topic

<table>
<thead>
<tr>
<th></th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Politics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All words</td>
<td>.85</td>
<td>.85</td>
<td>.85</td>
</tr>
<tr>
<td>Stop word removal</td>
<td>.82</td>
<td>.85</td>
<td>.79</td>
</tr>
<tr>
<td>Lead</td>
<td>.81</td>
<td>.84</td>
<td>.79</td>
</tr>
<tr>
<td><strong>Business</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All words</td>
<td>.67</td>
<td>.69</td>
<td>.65</td>
</tr>
<tr>
<td>Stop word removal</td>
<td>.66</td>
<td>.72</td>
<td>.61</td>
</tr>
<tr>
<td>Lead</td>
<td>.66</td>
<td>.71</td>
<td>.61</td>
</tr>
<tr>
<td><strong>Entertainment</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All words</td>
<td>.89</td>
<td>.86</td>
<td>.92</td>
</tr>
<tr>
<td>Stop word removal</td>
<td>.89</td>
<td>.85</td>
<td>.93</td>
</tr>
<tr>
<td>Lead</td>
<td>.89</td>
<td>.85</td>
<td>.92</td>
</tr>
<tr>
<td><strong>Other</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All words</td>
<td>.57</td>
<td>.73</td>
<td>.47</td>
</tr>
<tr>
<td>Stop word removal</td>
<td>.58</td>
<td>.67</td>
<td>.51</td>
</tr>
<tr>
<td>Lead</td>
<td>.55</td>
<td>.64</td>
<td>.47</td>
</tr>
<tr>
<td><strong>N/A</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All words</td>
<td>.88</td>
<td>.88</td>
<td>.88</td>
</tr>
<tr>
<td>Stop word removal</td>
<td>.88</td>
<td>.83</td>
<td>.94</td>
</tr>
<tr>
<td>Lead</td>
<td>.89</td>
<td>.82</td>
<td>.97</td>
</tr>
</tbody>
</table>

Markov Chains

To retrieve a closer examination of the Markov chains, Table 17 presents the probability distribution for every possible transition in terms of context. Each row shows the probability distribution for each possible combination of current (rows) and follow-up (columns) states. These probabilities were calculated from a total of 1,175,022 visits. For instance, search engines were on average followed by approximately 7 percent of the time by tabloid visits, 9 percent by broadsheet visits, and 9 percent by online-only outlets.
Table 16: Performance measures for the PAA algorithm per topic

<table>
<thead>
<tr>
<th>Topic</th>
<th>All words</th>
<th>Stop word removal</th>
<th>Lead</th>
</tr>
</thead>
<tbody>
<tr>
<td>Politics</td>
<td>0.85</td>
<td>0.82</td>
<td>0.81</td>
</tr>
<tr>
<td>Business</td>
<td>0.67</td>
<td>0.66</td>
<td>0.66</td>
</tr>
<tr>
<td>Entertainment</td>
<td>0.89</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>Other</td>
<td>0.57</td>
<td>0.58</td>
<td>0.55</td>
</tr>
<tr>
<td>N/A</td>
<td>0.88</td>
<td>0.88</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Table 17: Distribution Markov Chains in terms of context

<table>
<thead>
<tr>
<th>Current</th>
<th>Tabloid</th>
<th>Broadsheet</th>
<th>Online-only</th>
<th>International</th>
<th>Broadcaster</th>
<th>Search engine</th>
<th>Other</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabloid</td>
<td>50.58</td>
<td>0.34</td>
<td>1.16</td>
<td>0.05</td>
<td>0.29</td>
<td>0.04</td>
<td>3.33</td>
<td>3.54</td>
</tr>
<tr>
<td>Broadsheet</td>
<td>0.26</td>
<td>49.75</td>
<td>0.21</td>
<td>0.06</td>
<td>0.18</td>
<td>0.04</td>
<td>1.86</td>
<td>3.75</td>
</tr>
<tr>
<td>Online-only</td>
<td>0.26</td>
<td>0.07</td>
<td>53.23</td>
<td>0.33</td>
<td>0.40</td>
<td>0.00</td>
<td>0.18</td>
<td>5.42</td>
</tr>
<tr>
<td>International</td>
<td>0.49</td>
<td>0.08</td>
<td>0.27</td>
<td>28.08</td>
<td>0.14</td>
<td>0.02</td>
<td>0.24</td>
<td>7.69</td>
</tr>
<tr>
<td>Broadcaster</td>
<td>0.20</td>
<td>0.14</td>
<td>0.37</td>
<td>0.02</td>
<td>59.32</td>
<td>0.01</td>
<td>0.36</td>
<td>5.68</td>
</tr>
<tr>
<td>Facebook</td>
<td>4.02</td>
<td>2.41</td>
<td>1.28</td>
<td>2.72</td>
<td>1.97</td>
<td>0.00</td>
<td>16.12</td>
<td>NA</td>
</tr>
<tr>
<td>Twitter</td>
<td>1.16</td>
<td>1.15</td>
<td>0.03</td>
<td>0.71</td>
<td>0.26</td>
<td>0.00</td>
<td>1.21</td>
<td>NA</td>
</tr>
<tr>
<td>Search engine</td>
<td>6.84</td>
<td>8.61</td>
<td>9.3</td>
<td>8.04</td>
<td>13.43</td>
<td>2.63</td>
<td>20.47</td>
<td>0.18</td>
</tr>
<tr>
<td>Other</td>
<td>1.10</td>
<td>0.20</td>
<td>0.33</td>
<td>0.04</td>
<td>0.65</td>
<td>0.01</td>
<td>65.18</td>
<td>5.08</td>
</tr>
</tbody>
</table>

Table 18 presents the probability distribution for every possible transition in terms of content. Again, each row shows the probability distribution for each possible combination of current (rows) and follow-up (columns) states.

Table 18: Distribution Markov Chains in terms of content

<table>
<thead>
<tr>
<th>Current</th>
<th>Homepage</th>
<th>Politics</th>
<th>Business</th>
<th>Entertainment</th>
<th>Other</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homepage</td>
<td>21.58</td>
<td>5.58</td>
<td>11.40</td>
<td>47.76</td>
<td>2.55</td>
<td>4.70</td>
</tr>
<tr>
<td>Politics</td>
<td>16.18</td>
<td>7.93</td>
<td>11.29</td>
<td>40.42</td>
<td>1.23</td>
<td>3.06</td>
</tr>
<tr>
<td>Business</td>
<td>16.80</td>
<td>5.82</td>
<td>17.11</td>
<td>37.11</td>
<td>2.23</td>
<td>3.97</td>
</tr>
<tr>
<td>Entertainment</td>
<td>20.48</td>
<td>5.76</td>
<td>12.00</td>
<td>52.70</td>
<td>2.22</td>
<td>4.50</td>
</tr>
<tr>
<td>Other</td>
<td>10.34</td>
<td>4.25</td>
<td>9.97</td>
<td>34.80</td>
<td>4.45</td>
<td>3.73</td>
</tr>
</tbody>
</table>
Chapter 5

Figure 22: Correlations of news use across panel waves
Figure 23: Cross-lagged effects between news interest and political interest (unstandardized coefficients).

![Diagram of cross-lagged effects]

Note. N < 907, R² < .92, RMSEA < 0.000; CFI < 1.00 *p < .05. **p < .01. ***p < .001.

Note. Correlations between all exogenous variables as well as between error terms at each panel wave allowed, though not displayed in the figure.
### Table 19: Degree of overlap in news media use (Pearson’s $r$) in April 2020

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>1– Television news</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2– Current affairs shows</td>
<td>.61</td>
<td>.69</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3– Talk shows</td>
<td>.49</td>
<td>.69</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4– Quality newspapers</td>
<td>.10</td>
<td>.19</td>
<td>.16</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5– Tabloid newspapers</td>
<td>.19</td>
<td>.22</td>
<td>.23</td>
<td>.09</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6– Radio news</td>
<td>.21</td>
<td>.23</td>
<td>.23</td>
<td>.10</td>
<td>.12</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7– Online-only news websites</td>
<td>.10</td>
<td>.10</td>
<td>.18</td>
<td>.02</td>
<td>−.04</td>
<td>.08</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8– Online news websites</td>
<td>.14</td>
<td>.19</td>
<td>.19</td>
<td>.11</td>
<td>.38</td>
<td>.08</td>
<td>.30</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9– Non-mainstream news websites</td>
<td>.06</td>
<td>.19</td>
<td>.21</td>
<td>.19</td>
<td>.19</td>
<td>.10</td>
<td>.18</td>
<td>.28</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10– Opinion news websites</td>
<td>−.01</td>
<td>.09</td>
<td>.12</td>
<td>.12</td>
<td>.15</td>
<td>.05</td>
<td>.14</td>
<td>.20</td>
<td>.57</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11– Social media</td>
<td>−.01</td>
<td>.01</td>
<td>.06</td>
<td>−.07</td>
<td>−.01</td>
<td>−.01</td>
<td>.19</td>
<td>.18</td>
<td>.17</td>
<td>.20</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12– Mobile news apps</td>
<td>.12</td>
<td>.10</td>
<td>.10</td>
<td>.13</td>
<td>.02</td>
<td>.10</td>
<td>.41</td>
<td>.21</td>
<td>.15</td>
<td>.11</td>
<td>.21</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>13– Instant messaging apps</td>
<td>.13</td>
<td>.17</td>
<td>.17</td>
<td>−.02</td>
<td>.08</td>
<td>.07</td>
<td>.16</td>
<td>.14</td>
<td>.24</td>
<td>.22</td>
<td>.41</td>
<td>.26</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note. Correlations higher than .20 are highlighted.
### Table 20: Degree of overlap in news media trust (Pearson’s r) in April 2020

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1– Trust in public broadcasting</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2– Trust in commercial broadcasting</td>
<td>.67</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3– Trust in newspapers</td>
<td>.69</td>
<td>.58</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4– Trust in radio news</td>
<td>.74</td>
<td>.59</td>
<td>.70</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5– Trust in online news</td>
<td>.65</td>
<td>.52</td>
<td>.75</td>
<td>.70</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6– Trust in non-mainstream news websites</td>
<td>.15</td>
<td>.26</td>
<td>.19</td>
<td>.21</td>
<td>.22</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7– Trust in social media news</td>
<td>.16</td>
<td>.28</td>
<td>.18</td>
<td>.21</td>
<td>.22</td>
<td>.49</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>8– Trust in news received from others</td>
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*Note. Correlations higher than .30 are highlighted.*
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Authorship
Authorship

This section contains specific author contributions to the individual chapters, in order of contribution.

Chapter 2  •  Television news consumption
Researchers involved: Susan Vermeer (SV), Damian Trilling (DT), Sjoerd Stolwijk (SS), Sanne Kruikemeier (SK), and Claes de Vreese (CdV)

Conceptualization: SV, DT, SS, SK, CdV
Methodology: SV, DT
Data collection: SV, SS
Data analysis: SV
Writing (original): SV
Writing (review and editing): SV, DT, SS, SK, CdV
Visualization: SV
*This research was supported by Stichting KijkOnderzoek (SKO) and the Dutch Public Broadcaster (NPO).

Chapter 3  •  Online news consumption
Researchers involved: Susan Vermeer (SV), Damian Trilling (DT), Sanne Kruikemeier (SK), and Claes de Vreese (CdV)

Conceptualization: SV, DT, SK, CdV
Methodology: SV
Data collection: SV
Data analysis: SV
Writing (original): SV
Writing (review and editing): SV, DT, SK, CdV
Visualization: SV
*This research was supported by the Research Priority Area ‘Personalised Communication’ of the University of Amsterdam (funding acquisition: CdV).
Chapter 4 • **Mobile news consumption**

Researchers involved: Susan Vermeer (SV), Sanne Kruikemeier (SK), Damian Trilling (DT), and Claes de Vreese (CdV)

Conceptualization: SV, SK, DT, CdV
Methodology: SV
Data collection: SV*
Data analysis: SV
Writing (original): SV
Writing (review and editing): SV, SK, DT, CdV
Visualization: SV

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Chapter 5 • **News consumption in the digital society**

Researchers involved: Susan Vermeer (SV), Sanne Kruikemeier (SK), Damian Trilling (DT), and Claes de Vreese (CdV)

Conceptualization: SV, SK, DT, CdV
Methodology: SV
Data collection: SV*
Data analysis: SV
Writing (original): SV
Writing (review and editing): SV, SK, DT, CdV
Visualization: SV

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Digital technologies have dramatically changed the way citizens are informed about political and societal issues. Citizens can consume news anytime, anywhere, and from a wide range of sources on a growing number of devices.

Citizens, especially younger adults, are increasingly and predominantly using online and social media to get informed about the world around them. They are often directed to news that is sent, shared, or liked by their friends, family, and acquaintances.

Besides, citizens increasingly rely on algorithms that tailor search results or sort news based on digital traces of personal data. By analyzing citizens in an evolving media landscape, this dissertation tackles the question how content features, consumer features, and context features interact in shaping news exposure and, ultimately, citizens’ interest in politics and engagement with political news.