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# Covering Technology Risks and Responsibility: Automation, Artificial Intelligence, Robotics, and Algorithms in the Media

CORNELIA BRANTNER[1]
Karlstad University, Sweden

FLORIAN SAURWEIN
Austrian Academy of Sciences, Austria
University of Klagenfurt, Austria

Rapid technological advances in automation, algorithms, robots, and artificial intelligence (AI) entail risks, such as the loss of jobs, biases, and security threats, which raises questions about responsibility for the damage incurred by such risks and the development of solutions to ameliorate them. Because media play a central role in the representation and perception of technological risks and responsibility, this study explores the news coverage of automation. While previous research has focused on specific technologies, this study conducts a comprehensive analysis of the debate on automation, algorithms, robotics, and AI, including tonality, risks, and responsibility. The longitudinal media content analysis of three decades of Austrian news reports revealed that overall, the coverage increased, and it was optimistic in tone. However, algorithms were more frequently associated with risks and less positivity than other automation areas. Robotics received the most positive and the least risk-related coverage. Moreover, industry stakeholders were at the center of the responsibility network in the media discourse.

*Keywords: automation, artificial intelligence, AI, robotics, algorithms, responsibility, risks, media coverage, content analysis*

The economy and society are undergoing transformations that are increasingly shaped by robotics, algorithms, and artificial intelligence (AI). In short, developments in several social fields and economic sectors are centered on automation: Automated decision systems performing transactions in high-frequency trading; algorithms of search engines and social networks governing information dissemination on the Internet; self-driving cars and self-directed energy supplies in smart cities; and self-organized production networks in advanced manufacturing are examples for emerging applications of automation. Although

Cornelia Brantner: cornelia.brantner@kau.se
Florian Saurwein: florian.saurwein@oeaw.ac.at
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automation has a long history, automation technologies are now more autonomous and connected than ever before and pervasive in our lifeworld.

The trend toward automation has been accompanied by numerous changes and challenges, including expectations about fundamental transformations of human nature; changing paradigms of the organization of social, economic, and political systems; a revolution in the perception of time and space; and the transformation of habitats and mobility. Automation provides a broad range of potential benefits for social innovation, business optimization, and macroeconomic growth. However, it is also accompanied by several drawbacks that continue to attract public debate. Throughout its history, industrial automation has always been associated with the fear of job loss (Chace, 2018), but today, it is also increasingly associated with safety and security threats about human–machine interaction and the manipulation and abuse of autonomous technologies for economic or political purposes. Social media algorithms entail risks for democracy and the public sphere because they discriminate against certain users, enable automated propaganda, and may lead to political polarization (Ananny & Crawford, 2018; Murthy et al., 2016). Experts criticize data collection, profiling, social sorting, surveillance, and discrimination by automated systems (Christl & Spiekermann, 2016; Citron & Pasquale, 2014). Other risks result from the vastness of automated systems, which leads to the decreasing ability to control technology. Moreover, the emergence of the age of automation has raised concerns about its anthropological and ethical consequences (Anderson & Anderson, 2011; Coeckelbergh, 2020; Gunkel, 2012). Will humans be abolished by super-intelligent machines, or will they evolve into trans- or posthumans (Loh, 2018)? Do we need a new set of moral values and ethical principles?

The diffusion, influence, and risks of automation have also raised questions about the assignment and perception of responsibility (Loh & Loh, 2017; Sombetzki, 2014). This involves not only legal liability for damage but also the question of who is morally responsible for the problematic implications of automation and the governance of automation risks. However, the issues surrounding the allocation of responsibility are far from being resolved because the trend toward automation is accompanied by the emergence of new and challenging sociotechnical constellations. These are characterized by the interplay of multiple actors and (semi)autonomous "acting" technologies (Rammert, 2008). The delay in adapting legal frameworks and responsibility structures to keep pace with rapid technical development (e.g., Kroll et al., 2017) and determining how the responsibility for automation issues should be defined, enforced, and exercised has been frequently pointed out (Matthias, 2004; Waelbers, 2009). Who is held accountable if chatbots on the Internet make racist statements, if self-driving cars hit pedestrians, or if autonomous weapons kill people? Who must respond to a critical public if automated decision systems discriminate against certain groups? How is responsibility spread across actors about data security issues in complex interconnected multienterprise production networks of advanced manufacturing? Because of the growing importance of automation, it is a question of not only who assumes responsibility but also of the extent to which responsibility and responsible actors are publicly visible (Ouchchy, Coin, & Dubljević, 2020).

In the context of "uncertainty" about the risks and responsibilities of automation, media play a significant role. From a positive analysis perspective, media reporting contributes to shaping public perceptions and attitudes toward emerging technologies, such as robotics, AI, and algorithms (Chuan, Tsai, & Cho, 2019; Druckman & Bolson, 2011). Media reporting affects public knowledge about technologies and their acceptance, including the perception of risks and responsibility. From a normative perspective, media coverage of automation issues "is essential to the vibrant and critical discussion needed to confront this emerging public issue" (Brennen, Howard, & Nielsen, 2018, p. 1). Risks and concerns about emerging technologies require social and political debates based on the best available scientific knowledge (Scheufele & Krause, 2019). Companies often blame technology and refer to inevitable technical forces, economic imperatives, or political dynamics in responding to failures or hazardous developments; some refer to the self-responsibility of users, while others claim that the responsibility lies with companies and political actors (Saurwein, 2019). Media play the role of a seismometer in uncovering the risks of automation. Moreover, they have a control function that allows them to hold involved actors accountable (Sarcinelli, 2011). Subsequent empirical questions concern how the media portrays automation and how they represent automation risks and responsibility debates.

This study addresses these questions by employing a quantitative content analysis of news coverage on automation in Austrian media. It explores the amount of media reporting on automation issues, the realms of automation that attract media attention, the tone of news coverage on automation, and the risks described. In addition, it investigates the extent to which the media cover responsibility claims, which actors attribute responsibility, and which ones are held accountable in the automation debate.

## Media Coverage of Automation, Robotics, AI, and Algorithms

The present analysis of media reporting on automation risks and responsibility contributes to the research on the media coverage of new technologies and their controversial implications. Technology assessment has introduced concepts, such as "technology acceptance" and "technology controversies" (Hennen, 1999, p. 303), to analyze public discourses and citizens' perceptions of technologies. Moreover, communication science has established research lines, such as "risk communication" and "science communication," to explore public representations and perceptions of emerging technologies (Cacciatore et al., 2012; Scheufele & Krause, 2019). In this regard, there is a long tradition of the media content analysis of technology reporting (e.g., Kepplinger, 1994). As the following literature review shows, recurring issues in media content analyses include the amount and occasion of reporting, the relation between benefits and risks, media attitudes toward technologies, and covered actors.

Although automation has been subject to research and public debate for a while, we have not yet found any systematic analyses on the media coverage of "automation." There are, however, analyses that explore the media coverage of particular technologies that are strongly related to automation, such as AI, algorithms, and robots.

### *Frequency of Media Coverage and Its Development Over Time*

A starting point in understanding public perceptions of technologies is to examine the frequency of and trends in their coverage by media. Communication science suggests that a rise-and-fall cycle of many issues exists in media agendas. Empirical analyses of the media coverage of robotics and AI, however, have consistently found an increase in the volume of media reporting: Fast and Horvitz (2017) conducted a longitudinal analysis of the coverage of AI in *The New York Times* (1985–2015) and found "that discussion of AI has increased sharply since 2009" (p. 963). Chuan et al. (2019), in investigating coverage from 2009 to 2018, confirmed this finding and observed that a second peak had occurred since 2016. Sun, Zhai, Shen, and Chen (2020) investigated the coverage of AI in four U.S. and British newspapers from 1977 to 2019 and showed that media coverage "spiked drastically in recent five years" (p. 5). Similarly, Ouchchy et al. (2020) found an increase in the coverage of ethical issues about AI from 2013 to 2017, and in Italy, Righetti and Carradore (2019) saw a constant rise in news relating to robots from 2014 to 2018.

### *Tone Regarding Technology*

Another typical category for research on the media coverage of technology is the general tone of media articles on technology. Sentiment analysis is used to determine whether pessimistic or optimistic views predominate in the coverage of technology. Some have argued that media coverage alternates between two sensational poles: "utopian dreams of workless futures and eternal life, and dystopian nightmares of robot uprisings and the apocalypse" (Craig, 2018, as cited in Brennen et al., 2018, p. 2). Concerning AI and robotics, empirical analyses have indicated that, in general, a positive picture prevails (e.g., Javaheri et al., 2020; Zeng, Chan, & Schäfer, 2020). For example, Fast and Horvitz (2017) showed that AI coverage in *The New York Times* had consistently been more optimistic than pessimistic over a period of 30 years. Similarly, Garvey and Maskal (2019) revealed that U.S. news media covered AI with an overall positive tone. However, a positive tone was not observed in all types of coverage. Ouchchy et al. (2020), for example, found that the "initially optimistic and enthusiastic reporting" of ethical aspects of AI "was followed up by mostly critical or balanced tones in more recent years" (p. 933). Ficko, Koo, and Hyams (2017) found that the majority of articles about robotic surgery in U.S. newspapers (2010–15) were negatively biased.

### *Benefits, Risks, and the Framing of Technology*

Recurring issues in analyses of media reporting on technology are the coverage of particular benefits and risks and the framing of specific technologies. Chuan et al. (2019) and Sun et al. (2020) found that in the U.S. media and U.S. and British media, respectively, the framing of AI as beneficial, such as providing economic benefits and improving human lives, was more prevalent than framing it as risky. The most frequently discussed risks included the shortcomings of the technology, the loss of jobs, and privacy concerns. According to Fast and Horvitz (2017), fear of loss of AI control, ethical concerns about AI, and its negative impact on work have increased in recent years, in parallel with the increasing coverage of AI in health care and education. Ouchchy et al.'s (2020) analysis of media reporting on AI ethics revealed three main issues: undesirable results, accountability, and a lack of ethics. Regarding AI discourse in China, Zeng et al. (2020) demonstrated that the economic frame was predominant in reporting by the Communist party's outlet, *People's Daily*, and in debates in the social medium WeChat; however, the critical socioethical frame was nonexistent in the former medium and declining in the latter. Laryionava and Gross (2012) found that health care robots were "mostly portrayed as assistants, colleagues, or even friends" (p. 265), but only a small number of articles raised ethical concerns. These previous studies analyzed the coverage of robots and AI. However, reporting on the benefits and risks of algorithms, to the best of our knowledge, has been examined only by Barn's (2019) study on UK media. He found that the two predominant ethical concerns about algorithms were unfair outcomes (discrimination) and the nontransparency and inaccessibility of algorithmic processes.

### *Speakers and Actors*

Media content analyses frequently assess the appearance of actors in media discourses. In general, a greater visibility of a stakeholder is associated with greater influence (Ferree, Gamson, Rucht, & Gerhards, 2002; Gerhards & Schäfer, 2009), and a more diverse set of speakers is associated with more controversial discourse. For example, in the U.S. media's general technology coverage from 1986 to 2013, Allen and Castro (2017) found that claims about technology problems were more likely to be made by civil society and government actors than by industry actors.

Among the previous studies on the reporting of AI, robotics, and algorithms, however, only a few analyzed the actors represented. Sun et al. (2020) observed that U.S. media discourse about AI was dominated by business-related actors, especially Internet giants (e.g., Google and Facebook), compared with actors in research and government. Missing were "the voices from stakeholders such as ordinary citizens, anti-AI activists" (Sun et al., 2020, p. 13). Similarly, Brennen et al. (2018) found a strong influence of industry on AI coverage in UK news, based on the predominance of industrial topics and industry-connected sources, which led to the portrayal of AI as a competent solution to a range of public problems. However, they also noted that by being consistently indexed to industry sources and concerns, the media limited the range of voices included and lacked "acknowledgement of ongoing debates concerning AI's potential effects" (Brennen et al., 2018, p. 1). Public discourse would benefit from more alternative, independent, and controversial views of scientists and civil society actors (Brennen et al., 2018; Sun et al., 2020). This argument is strongly reminiscent of the normative deliberative model of the public sphere (Habermas, 1989), which requires the participation of civil society actors in a functioning discursive public sphere.

### *Attribution of Responsibility*

Although there has been ongoing academic and legal debate on the responsibilities surrounding automation, research has seldom raised the question of how media report on these responsibilities. An exception is Suárez-Gonzalo, Mas-Machón, and Guerro-Solé's (2019) study, which investigated how the failure of Microsoft's machine learning chatbot Tay—which was terminated after it began producing hate posts—was framed by international news media in 2016 and to whom the media assigned responsibility for this failure. They found that the news coverage blamed the machine learning code or interactions between humans and Tay's software for the failure. Twitter users were identified as the agents responsible more than twice as often as Microsoft was blamed. The media failed to clarify the responsibilities that should be assumed by users, designers, and the owners of the platforms on which robots perform their actions. Finally, Suárez-Gonzalo et al. (2019) emphasized that the media had adopted Microsoft's reasoning that the company bears "no responsibility" for the incident (p. 10).

While there is a lack of research on responsibility in automation issues, systematic previous research has examined media coverage of responsibility in the context of other social controversies. For example, Iyengar (1996) and Gerhards, Offerhaus, and Roose (2007) examined responsibility in the

European system of multilevel governance. Post, Kleinen-von Königslöw, and Schäfer (2019) investigated the assignment of responsibility for climate change. These approaches provided the conceptual and methodological foundations of our analysis.

## Research Questions and Hypotheses

This study contributes to the research on automation by conducting an empirical analysis of the coverage of risk and responsibility in the Austrian media. Drawing on existing evidence, we raised the following research questions. Based on our review of the relevant literature, we formulated hypotheses that guided the analysis:

### *Coverage of Automation*

*RQ1: To what extent do media report on automation, which automation realms are in the media focus (robotics, AI, algorithms), and have patterns of media coverage changed over time?*

Previous investigations consistently found an increase in the media coverage of robotics and AI (Fast & Horvitz, 2017; Ouchchy et al., 2020; Righetti & Carradore, 2019; Sun et al., 2020); we therefore expect that the volume of news about automation in Austria has also increased (H1).

### *Attitude Toward Automation*

*RQ2: Is media reporting on automation positive/optimistic or negative/pessimistic in tone, and are there differences in the tone of reports on different realms?*

Empirical analyses of reports on AI and robotics indicated that a positive picture prevails (e.g., Fast & Horvitz, 2017; Garvey & Maskal, 2019; Javaheri et al., 2020). We therefore assume that Austrian media reporting on automation issues is also predominantly positive in tone (H2).

### *Coverage of Automation Risks*

*RQ3: To what extent do media reports on automation address risks, which risks are subject to media reporting, are there differences in the extent of risk coverage for different automation realms, has the extent of risk coverage changed over time, and do articles covering risks tend to be negative in tone?*

There is evidence that media cover a broad range of different automation risks. Some analyses have also found an increase in the media coverage of AI risks and concerns (Fast & Horvitz, 2017; Ouchchy et al., 2020), as well as critical media coverage of algorithms because of their ethical implications (Barn, 2019). We therefore expect that Austrian media also cover a broad range of different risks, that the references to risks are increasing (H3a), and that articles covering risks are more negative in tone (H3b). Barn's (2019) observation and our impression of media reporting in recent years have led to the hypothesis that the coverage of algorithms, in particular, is associated with risks (H3c).

### *Coverage of Responsibility*

Automation issues raise questions about the attribution and perception of responsibility (Loh & Loh, 2017). Consequently, we ask:

*RQ4: To what extent does media reporting on automation also encompass assignments of responsibility, and are there differences in the extent of responsibility assignments for different automation realms?*

Moreover, we expect that the extent of responsibility attributions has grown over time (H4a) and that articles covering responsibility issues are more negative in tone (H4b).

### *Actors in the Responsibility Network*

*RQ5: Which actors (industry, politics, media, scientists, civil society, users, etc.) have a say in assigning responsibility, and which actors are held accountable for automation risks and the development of solutions? To what extent are scientific actors, civil society actors, and news media involved in the responsibility network as speakers and addressees/assignees of responsibility claims?*

There is little previous research on the coverage of responsibility in the automation discourse, and only a few studies (Brennen et al., 2018; Sun et al., 2020) have explored the composition of speakers more generally. Because these analyses indicate that media discourses have been dominated by industry/business actors, we assume that industry actors are the most visible stakeholder group in the assignment of responsibility (H5).

## Methods

### *Procedure and Reliability Checks*

This study used the Austrian Media Corpus (AMC), which contains articles drawn from the main Austrian news media, including daily and weekly national and regional newspapers, news magazines, and transcriptions of daily broadcasting newscasts. To identify the relevant articles, we first defined keywords that indicated media reporting on automation issues. While the debate is often centered on the umbrella term "automation," automation issues are also associated with particular technologies, such as robotics, AI, and algorithms. We therefore used an automated keyword search to identify all media reports that explicitly (at least once) referred to robots/robotics, AI, algorithms, or automation.[2] The search led to a subcorpus of 45,034 articles published from 1991 to 2018, which provided the basis for the content analysis.[3] Because

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[2] The full-text search was conducted by a word and lemma search for German expressions for automation/automatization (Automatisierung), robots/robotics (Roboter*, Robotik), algorithms (Algorithmen), and artificial intelligence (künstlich* Intelligenz; Artificial Intelligence).

[3] The data collection began in 1991 with the inclusion of national newspapers. During the 1990s, other media were successively included. Since 2000, the AMC has added between 300 million (2000) and 411 million (2011) articles per year; for 2018, the final year of investigation, it contains 361 million articles.

every news article, regardless of whether it was a short news item, a background report, or an opinion piece, contributed to the public image of technologies, all genres were included.

In the second step, a representative random sample of 1,500 articles was selected, of which 200 articles were randomly chosen to deductively–inductively develop the coding scheme. That is, we derived categories from the existing literature and adapted and expanded the coding instrument based on this subsample. In this sample, 158 articles dealt with automation as either the main or ancillary item; the remaining 42 articles were either false positives (*n* = 7; e.g., one referred to ski-jumpers "automating the jumping process"), or they contained only minor references to automation (*n* = 35), such as a listing of the film *A.I.* in the TV program section. Of the 158 articles, 98 were used in coder training and 60 were used in the pilot intercoder reliability assessment. Of the 42 articles that were not subjected to coding, 27 were used in coder training because it was important to identify them correctly. The remaining 15 articles were presented to the coder, in addition to the 60 articles that addressed automation. The coder, a graduate project assistant, correctly identified the 15 articles and coded the 60 articles, which were then used in the pilot intercoder reliability test, which yielded satisfactory coefficients (see the online Appendix[4] for pilot and final reliability assessment). Before the detailed coding, the remaining 1,300 articles were read carefully. Articles that were excluded from coding were noted about whether they contained only minor references to automation or false positives.[5]

To comply with the general recommendation that the subsample used in reliability testing should be at least 10% of the total sample (Neuendorf, 2017), the first author coded a further 60 items drawn from the total sample after the project assistant had completed the coding. Following Neuendorf (2017), the articles were selected by combining the rich-range and probability subsample strategies. The rich-range strategy was used to increase the number of cases containing risks and responsibility attributions in the test data. Percentage of agreement and Krippendorf's alpha coefficients in the final reliability assessment were satisfactory for all variables, ranging between 93% and 100% and .85 and 1, respectively. They are reported in the Appendix (see footnote 4).

### *Coding*

Of the 1,500 articles, 1,176 dealt with automatization, robotics, algorithms, or AI as the main or ancillary topic; thus, they were subject to coding. If automation issues were the main topic, the entire article was the coding unit for the categories measuring the automation realm and the attitude toward automation. If automation was an ancillary item, the coding unit was limited to the part of the text where automation was covered. Risks and assignments of responsibility were coded at the statement/claim level.

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Thus, the corpus, measured by the number of articles, has been representative of the Austrian media landscape only since 2000. This must be considered in examining trends in coverage frequency.

[4] https://www.dropbox.com/s/zi919ztjpltmrwu/Appendix_MS_ID17054.pdf

[5] Identification was necessary as they are to be included in a subsequent study that applies machine learning to the whole sample.

*Attitude Toward Automation*

We coded the attitude toward automation as positive, fairly positive, ambivalent (a balance between positive and negative arguments), fairly negative, negative, or neutral (no attitude toward automation). For the analysis, the coding was transformed into a 5-point scale ranging from −2 (*negative*) to +2 (*positive*), and a value of 0 was assigned to both ambivalent and neutral items.

*Automation Realm*

The automation realm was coded by differentiating between AI, robots/robotics, algorithms, and automation in general (for clarity, this category was called "automatization").

*Risks*

Risks were coded at the statement/claim level. Table 2 provides the deductively–inductively developed list of 21 different risks. If a specific risk was mentioned several times in an article, it was coded several times. However, for the analysis, it was dichotomously recoded if a specific risk was present or absent in an article.

*Assignment of Responsibility*

Each complete assignment of responsibility (whether directly or indirectly cited or made by a journalist or guest author) within an article was coded separately at the statement/claim level. The completeness of a responsibility assignment was determined by its semantic content: the coding unit was any single responsibility claim where someone was held responsible for damage or a problem (or its solution) or where someone was called to act to prevent future damage or to rectify an existing problem. First, we coded who (assigning actor/speaker) assigned responsibility to whom (subject actor/addressee). An actor was an organization, institution, or collective, its representative or spokesperson, or an individual who did not represent any organization/institution/collective. In coding, the decisive factor was the role in which an actor was represented in the article. For both variables, in assigning party/speaker and subject actor/addressee, we differentiated the following: (1) political, (2) judiciary, (3) economic/industry, (4) scientific or educational, (5) media, (6) (civil) society, and (7) individual actors. "(Civil) society" was coded if the speaker or addressee was an activist or belonged to an NGO or advocacy group, or was such an organization or group. However, concerning the addressee, this code was also used if responsibility was assigned to society at large. "Individual" was coded for assigning actors who did not speak for a collective, such as authors of readers' letters, interviewed consumers, and parents. Accordingly, for the addressee variable, the code "individual" was used when responsibility was assigned to individuals (e.g., to individual users of technologies, or parents).

*Mode*

In addition, the mode was coded—that is, whether speakers assigned responsibility to a third party (external attribution) or to themselves (self-attribution).

## Results

### *Amount of and Trends in the Media Coverage of Automation (RQ1)*

The results of the longitudinal analysis of media reporting support the assumption (H1) that media coverage of automation has increased over time, particularly since 2015. However, as Figure 1 shows, the media coverage of the four "realms" of automation was not equally distributed. Over time, robotics gained significantly more media attention (56.6%) than did automatization (18.6%), AI (15.1%), and algorithms (9.7%). While growth was observed in all four automation realms, the strong increase in media reporting on AI since 2016 was particularly striking. Almost three-quarters of all articles on AI had appeared in the most recent three years of the investigation, and almost 40% of them were published in 2018.

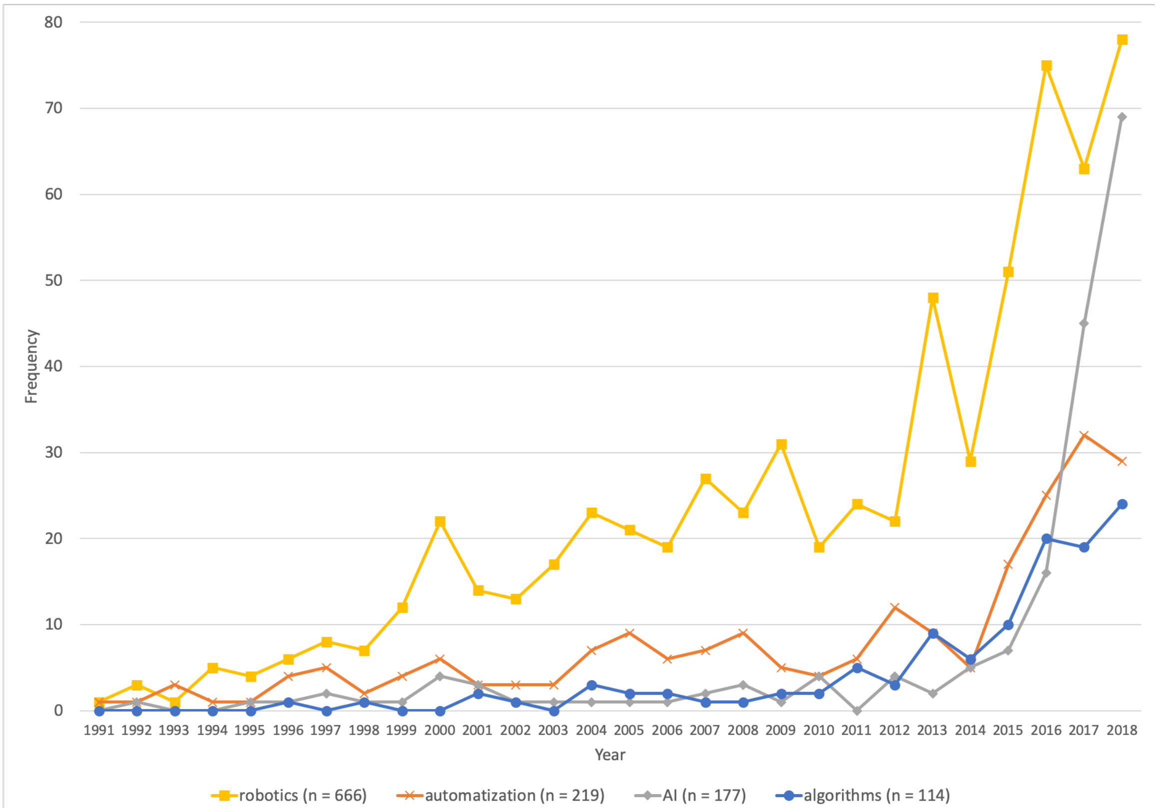



***Figure 1. Amount of media coverage by automation realm (1991–2018).***
*Note*. *N* = 1,176. Since the AMC database has been fully representative of the Austrian media landscape only since 2000 (see footnote 3), frequency trends can be interpreted only from 2000 onward.

### *Attitude Toward Automation (RQ2)*

Almost half of the 1,176 articles described automation positively (33.4%) or fairly positively (10.5%), only one-sixth were negative (11.2%) or fairly negative (5.4%) in tone, 4.8% were ambivalent about automation issues, and more than a third were neutral and did not include an evaluation (34.7%). The mean score of all articles—based on the 5-point scale from −2 to +2—is 0.49 (see Table 1). As expected, these results indicated that Austrian readers were confronted with a positive and optimistic, rather than a pessimistic, media portrayal of automation (H2).

Using tone as the dependent variable and automation realm as the independent variable, the analysis of variance (ANOVA) showed that although the overall attitude toward automation was positive, the tone differed significantly depending on which particular technology was the focus of the article (see Table 1): $F_W(3, 329) = 5.36$, $p = .001$, $\omega^2 = 0.015$.[6] Planned contrasts revealed that articles focusing on

[6] As equal variances are not assumed, the Welch test for equality of means was employed.

algorithms ($M$ = .01, $SD$ = 1.53) had a significantly less positive attitude toward technology than those focusing on other automation realms: $t(138) = 3.34$, $p = .001$, $r = 0.27$.[7] A closer analysis of the articles showed that more negative attitudes toward algorithms were mainly because in recent years, the power of algorithms and their shortcomings, such as bias and nontransparency, have been the subject of both academic debate and critical media coverage.

***Table 1. Attitudes Toward Different Automation Realms.***

| Automation Realm | *n* | *M* | *SD* |
|---|---|---|---|
| Algorithms | 114 | .01 | 1.53 |
| Automatization | 219 | .55 | 1.36 |
| AI | 177 | .40 | 1.27 |
| Robotics | 666 | .58 | 1.23 |
| Total | 1,176 | .49 | 1.30 |

*Note. Scale: −2 (negative), −1 (fairly negative), 0 (ambivalent or neutral (no tonality)), 1 (fairly positive), 2 (positive).*

***Coverage of Risks (RQ3)***

Risks were repeatedly the subject of media reporting on automation. Almost 40% (39.2%) of news articles mentioned at least one type of risk: There were 891 mentions of risks in 462 articles.

The analysis identified 21 different risks in total, which demonstrated a broad spectrum of concerns about automation (see Table 2). Specifically, more than half of all mentions referred to one of the top five risks: (1) shortcomings of the technology; (2) loss of jobs; (3) ethical, moral, or philosophical concerns; (4) loss of human autonomy and control; and (5) lack of adaptation on the part of the industry, economy, or political economy.

The list of 16 additional but less frequently mentioned risks included the following: (6) safety risks; (7) lack of user literacy or lack of adaptation on the part of the education system; (8) data protection, privacy concerns, and surveillance; (9) threats to sociality (including alienation from the natural environment, threats to the meaning of life, uncanny valley); and (10) embedded bias (i.e., manipulation, distortion, falsehood, filter bubbles, polarization, and censorship).

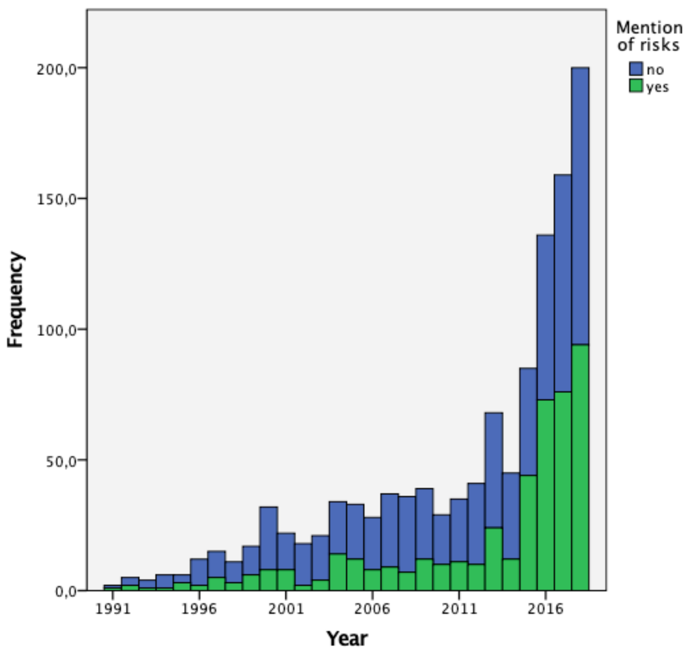
[7] Individual pairwise planned contrasts tests showed significant mean differences between algorithms and the three other groups—that is, with automation ($p = .002$), AI ($p = .024$), and robotics ($p < .001$), but not between all other groups. The more conservative Tamhane's T2 post hoc tests showed that the algorithms' mean differed significantly from those of automatization ($p = .01$) and robotics ($p = .001$), but not from the AI mean.

***Table 2. Share of Reporting on Different Types of Automation Risks.***

| Types of Risks | *n* | % of Responses | % of Cases |
|---|---|---|---|
| Shortcomings of the technology | 162 | 18.2 | 35.1 |
| Loss of jobs | 101 | 11.3 | 21.9 |
| Ethical, moral, or philosophical issues | 81 | 9.1 | 17.5 |
| Loss of human autonomy, sovereignty, and control | 79 | 8.9 | 17.1 |
| Lack of adaptation by the industry, economy, economic policy | 63 | 7.1 | 13.6 |
| Safety risks | 48 | 5.4 | 10.4 |
| Lack of user literacy/lack of adaptation in the education system | 46 | 5.2 | 10.0 |
| Data protection, privacy concerns, and surveillance | 41 | 4.6 | 8.9 |
| Threats to sociality | 39 | 4.4 | 8.4 |
| Embedded bias | 37 | 4.2 | 8.0 |
| Economic efficiency, investment risks | 30 | 3.4 | 6.5 |
| Abuse of AI, algorithms by the state, companies, interest groups | 27 | 3.0 | 5.8 |
| In-transparency (black box) | 24 | 2.7 | 5.2 |
| Discrimination, inequality | 23 | 2.6 | 5.0 |
| Market power, monopolization | 20 | 2.2 | 4.3 |
| Liability, responsibility | 19 | 2.1 | 4.1 |
| IT-/KI-security (against hackers, etc.) | 15 | 1.7 | 3.2 |
| Inequality of social security contributions, tax justice | 13 | 1.5 | 2.8 |
| Economic efficiency, shortcomings in productive efficiency | 13 | 1.5 | 2.8 |
| Commodification | 9 | 1.0 | 1.9 |
| Economic efficiency, misallocation of resources | 1 | 0.1 | 0.2 |
| Total | 891 | 100.2* | 192.7 |

*Note. N* = 891 mentions of risks in 462 articles; *rounding error.

Moreover, the analysis confirmed that the coverage of automation risks increased as the media reporting on automation increased (H3a). Figure 2 shows that the proportion of articles in which automation risks were discussed fluctuated over time. Nevertheless, with the increase of reporting on automation since 2015, the proportion of articles that mentioned risks also increased. Hence, not only automation but also the accompanying risks have been increasingly present in the public debate since 2015, when the share was always around 50%.




| | Risks | | |
|---|---|---|---|
| | No | Yes | Total |
| Year | % | % | *n* |
| 1991 | 50.0 | 50.0 | 2 |
| 1992 | 60.0 | 40.0 | 5 |
| 1993 | 75.0 | 25.0 | 4 |
| 1994 | 83.3 | 16.7 | 6 |
| 1995 | 50.0 | 50.0 | 6 |
| 1996 | 83.3 | 16.7 | 12 |
| 1997 | 66.7 | 33.3 | 15 |
| 1998 | 72.7 | 27.3 | 11 |
| 1999 | 64.7 | 35.3 | 17 |
| 2000 | 75.0 | 25.0 | 32 |
| 2001 | 63.6 | 36.4 | 22 |
| 2002 | 88.9 | 11.1 | 18 |
| 2003 | 81.0 | 19.0 | 21 |
| 2004 | 58.8 | 41.2 | 34 |
| 2005 | 63.6 | 36.4 | 33 |
| 2006 | 71.4 | 28.6 | 28 |
| 2007 | 75.7 | 24.3 | 37 |
| 2008 | 80.6 | 19.4 | 36 |
| 2009 | 69.2 | 30.8 | 39 |
| 2010 | 65.5 | 34.5 | 29 |
| 2011 | 68.6 | 31.4 | 35 |
| 2012 | 75.6 | 24.4 | 41 |
| 2013 | 64.7 | 35.3 | 68 |
| 2014 | 73.3 | 26.7 | 45 |
| 2015 | 48.2 | 51.8 | 85 |
| 2016 | 46.3 | 53.7 | 136 |
| 2017 | 52.2 | 47.8 | 159 |
| 2018 | 53.0 | 47.0 | 200 |
| Total | 60.7 | 39.3 | 1,176 |

***Figure 2. Frequency of total articles by year and risks.***

*Note.* $N$ = 1,176. Green parts of the bars indicate articles containing risks; binary logistic regression: Constant (B = −106.13, $SE$ = 19.69), year (B = .05, $SE$ = .01), exp(b) = 1.05, 95% CI [1.03, 1.07], Cox and Snell $R^2$ = .03, Nagelkerke's $R^2$ = .04, $\chi^2(1) = 30.79$, $p$ <. 001.[8]

An independent-samples $t$ test demonstrated that the attitude toward automation was less positive if risks were covered in the articles ($M$ = −.13, $SD$ = 1.42, $N$ = 462) compared with articles that did not mention any risks ($M$ = .90, $SD$ = 1.04, $N$ = 714), $t(778.563) = -13.485$, $p < .001$, 95% CI [−1.18, −.88], $r$ = .44 (assuming unequal variance), which thus supported the assumption that the coverage of risks was correlated with a more negative/critical tone of reporting (H3b).

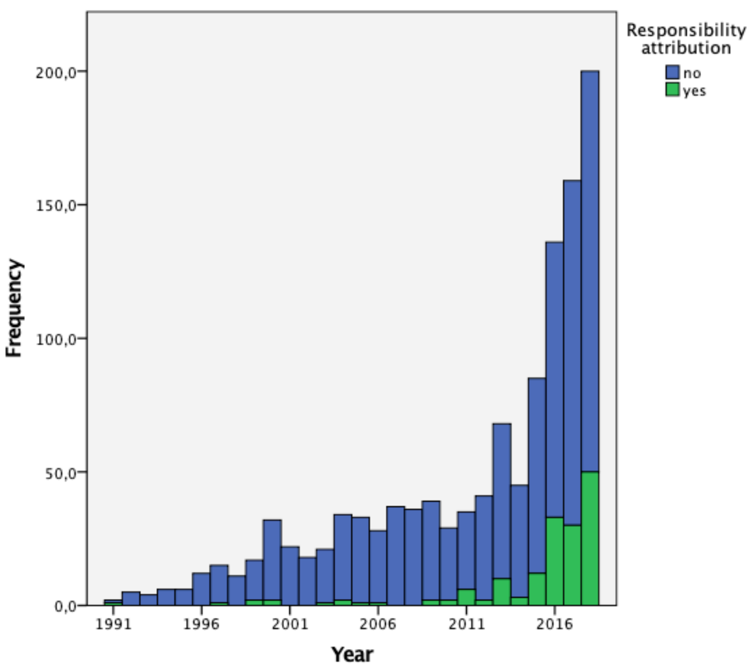
Finally, the chi-square test of the four automation realms with the presence/absence of risks revealed significant differences: $\chi^2(3, N = 1176) = 46.097$, $p < .001$; Cramer's V = .198. These results

[8] Binary logistic regression was used to explore the relation between coverage years and the presence/absence of risks. It is an appropriate technique for predicting the presence or absence of the outcome of a dichotomous dependent variable (Neuendorf, 2017). Cox and Snell is a conservative measure and Nagelkerke a liberal measure of pseudo-$R^2$, which is used to calculate the strength of the relationship. An odds ratio (exp(b)) of 1.05 meant that an article was 1.05 times more likely to cover a risk per 1 unit rise in years.

support our assumption that the share of risks is higher in the coverage of algorithms (H3c). While 61.4% of reports on algorithms addressed the risks of technology, less than one-third of reports on robotics (31.8%) and less than half of those on automatization (43.4%) and AI (48.0%) did so.

### *Assignment of Responsibility (RQ4)*

Automation issues raise questions about the assignment and perception of responsibility. The results show that compared with risks, the responsibility for problems and solutions was assigned less often. The analysis identified 296 responsibility claims in 161 articles. Thus, 13.7% of all articles contained one or more responsibility claims. Not all articles dealing with technology risks also contained responsibility claims; 68.2% of the articles dealing with risks did not include responsibility, but almost all articles (91%) that contained responsibility claims also covered risks.




| | Responsibility Attribution | | |
|---|---|---|---|
| Year | No % | Yes % | Total *n* |
| 1991 | 50 | 50 | 2 |
| 1992 | 100 | | 5 |
| 1993 | 100 | | 4 |
| 1994 | 100 | | 6 |
| 1995 | 100 | | 6 |
| 1996 | 100 | | 12 |
| 1997 | 93 | 7 | 15 |
| 1998 | 100 | | 11 |
| 1999 | 88 | 12 | 17 |
| 2000 | 94 | 6 | 32 |
| 2001 | 100 | | 22 |
| 2002 | 100 | | 18 |
| 2003 | 95 | 5 | 21 |
| 2004 | 94 | 6 | 34 |
| 2005 | 97 | 3 | 33 |
| 2006 | 96 | 4 | 28 |
| 2007 | 100 | | 37 |
| 2008 | 100 | | 36 |
| 2009 | 95 | 5 | 39 |
| 2010 | 93 | 7 | 29 |
| 2011 | 83 | 17 | 35 |
| 2012 | 95 | 5 | 41 |
| 2013 | 85 | 15 | 68 |
| 2014 | 93 | 7 | 45 |
| 2015 | 86 | 14 | 85 |
| 2016 | 76 | 24 | 136 |
| 2017 | 81 | 19 | 159 |
| 2018 | 75 | 25 | 200 |
| Total | 86 | 14 | 1,176 |

***Figure 3. Frequency of total articles by year and responsibility attribution.***

*Note*. $N$ = 1,176. Green parts of the bars indicate articles containing responsibility attributions; binary logistic regression: Constant (B = −284.94, $SE$ = 42.57), year (B = .14, $SE$ = .02), exp(b) = 1.15, 95% CI [1.10, 1.20], Cox and Snell $R^2$ = .05, Nagelkerke's $R^2$ = .1, $\chi^2(1)$ = 65.68, $p$ <. 001.[9]

[9] See footnote 7.

Figure 3 demonstrates that while the proportion of articles that contained responsibility claims averaged 13.7% over all years, it increased to 19% or higher since 2016, peaking in 2018, when one in four articles dealt with responsibilities. Thus, responsibility claims were more frequently included in the more recent public debate (H4a).

Moreover, the number of responsibility claims differed across automation realms. They were present more often in the context of reporting on algorithms than in the context of reporting on other technologies. Responsibility was addressed in only 7.1% of articles about robotics, and in nearly one in five articles on automatization (19.2%) and AI (18.1%), but in more than a third of articles on algorithms (35.1%); $\chi^2(3, N = 1176) = 77.439$, $p < .001$, Cramer's V = .257.

Similar to the coverage of risks, the results showed a more negative tone about automation in reporting on responsibility. Articles covering responsibility were more negative in tone ($M = -.11$, $SD = 1.42$, $N = 161$) compared with articles that did not refer to responsibility ($M = .59$, $SD = 1.25$, $N = 1{,}015$), $t(201.981) = 5.928$, $p < .001$, 95% CI [−.94, −.47], $r = 0.38$ (assuming unequal variance). Thus, H4b was supported.

### ***Responsibility Network of Actors and Addressees (RQ5)***

As expected, the main assignees (addressees) of responsibility were actors in economics and industry (44.6%)—for example, social media proprietors such as Facebook, producers of autonomous cars, or advanced manufacturing companies that used automated production lines (see Table 3 and Figure 4). Political actors ranked second: Roughly a quarter of responsibility claims were directed at the political system (23.3%). This was followed by the assignment of responsibility to the society (14.5%). For example, a history professor called for society to think about how robots and AI could coexist with humans in an ethical and humane way (Reinalter, 2018).

Individuals (6.8%) were held responsible almost as frequently as science and education were (7.4%). For example, Siegel (2015), quoting Jason Lanier, stated that individual users were responsible for being commodified into products of the algorithms of Internet companies. The assignments of responsibility to science and education have included calls for their better understanding of big data and algorithms to break the powerful influence of Internet corporations and to enable a more pluralistic society (Stanzl, 2016).

Journalists and legacy media (2.0%) were rarely held accountable, but when they were, it was often in connection with social media algorithms. For example, a communication scholar called on journalists to educate users about the mechanisms of social media and their algorithmically generated news feeds (Schnizlein & Steinlechner, 2016). Interestingly, legal bodies were rarely called to account (1.4%) in media coverage of automation.

***Table 3. Responsibility Network.***

| | Subject of responsibility (*n* and % within subject) | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Politics | | Economy | | Science | | Journalist | | Judiciary | | (Civil) Society | | Individual | | Total | |
| Assigning party | *n* | % | *n* | % | *n* | % | *n* | % | *n* | % | *n* | % | *n* | % | *n* | % |
| Politics | 7[a] | 10.1 | 6 | 4.5 | 2 | 9.1 | 0 | 0 | 0 | 0 | 1 | 2.3 | 0 | 0 | 16 | 5.4 |
| Economy | 15 | 21.7 | 66[a] | 50.0 | 1 | 4.5 | 0 | 0 | 2 | 50.0 | 5 | 11.6 | 7 | 35.0 | 96 | 32.4 |
| Science | 25 | 36.2 | 21 | 15.9 | 13[a] | 59.1 | 3 | 50.0 | 1 | 25.0 | 22 | 51.2 | 6 | 30.0 | 91 | 30.7 |
| Journalists | 15 | 21.7 | 27 | 20.5 | 6 | 27.3 | 2[a] | 33.3 | 1 | 25.0 | 8 | 18.6 | 4 | 20.0 | 63 | 21.3 |
| Civil society | 6 | 8.7 | 9 | 6.8 | 0 | 0 | 1 | 16.7 | 0 | 0 | 7[a] | 16.3 | 3 | 15.0 | 26 | 8.8 |
| Individuals | 1 | 1.4 | 3 | 2.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 1.4 |
| Total | 69 | 100 | 132 | 100 | 22 | 100 | 6 | 100 | 4 | 100 | 43 | 100 | 20 | 100 | 296 | 100 |
| % of total subjects | | 23.3 | | 44.6 | | 7.4 | | 2.0 | | 1.4 | | 14.5 | | 6.8 | | |

[a]Attributions to one's own system can be external or self-attributions; number of self-attributions: politics = 6, economy = 37, science = 10, journalists = 2, civil society = 6.

With regard to actors (speakers) who expressed the assignment of responsibility, we found that actors in economics (32.4%) and science and education (30.7%) had almost an equal say. Journalists were also important contributors to the debate, as every fifth responsibility assignment was made by them (21.3%). Interestingly, civil society actors (8.8%) appeared more frequently as speakers in the debate than politicians (5.4%) did, and nonaffiliated individuals (1.4%) were seldom covered by the media. Overall, speakers from industry did not outnumber speakers from other groups. Thus, H5 was not supported.

However, Figure 4 clearly shows that industry actors played a central role in the responsibility network. Interestingly, this centrality resulted, inter alia, from a high share of self-referentiality among economic actors about the accountability for automation. When economic actors assigned responsibility (96 cases), they called into account their own field in more than two-thirds of the cases (69%). Half of all responsibility assigned to the economic field was expressed by economic actors, and they showed a high share of self-attribution. Although scientists spoke about automation responsibility almost as frequently as economic stakeholders did, they were seldom held to account. Moreover, their self-referentiality was much lower, but when they referred to their own system, they usually addressed their own responsibility (10 of 13 cases). Finally, the following two observations were striking: (1) while political actors had little active say in the media, they were often the assignees of responsibility claims, especially in their role as legislators; (2) automation issues were relatively frequently perceived as the responsibility of society in general.

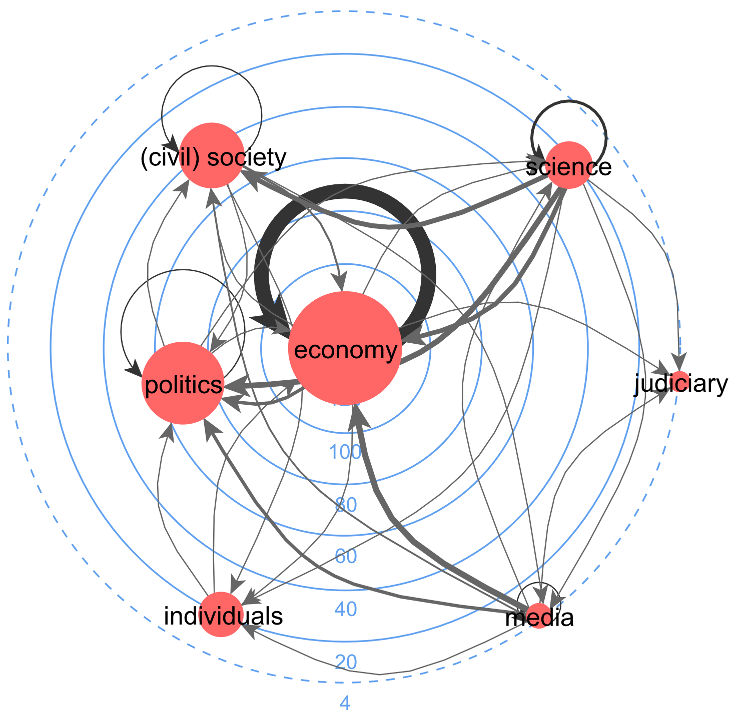



***Figure 4. Directed actor network.***

*Note*. The directed network consisting of *N* = 296 coded responsibility attributions (see Table 3) was calculated and visualized using Visone (http://visone.info/). The speakers/assigning parties are the sources (starting node) in the directed network, and the subjects of responsibility are the targets (ending node). Their relationship (called edge) is indicated by the arrows. Node size and position are weighted by in-degree centrality (Freeman, 1978/1979), including self-loops: the higher the in-degrees, the larger the node and the more central a node is positioned within the concentric circles; the in-degree centrality is determined by the number of mentions of an ending node (responsibility subject/addressee) in the network. The thicker the arrows (outgoing edges), the more often the respective speakers (starting nodes) mentioned the respective subjects (ending nodes). Round arrows around nodes show self-loops. A self-loop represents attributions to one's own system, which can arise either through self-attribution (actors holding themselves responsible) or through external attribution (other actors from the same system are held responsible).

## Summary and Conclusions

This article contributes to the body of research on the reporting of automation technology. A quantitative content analysis of Austrian media coverage between 1991 and 2018 was conducted. The results showed the amount of media reporting on automatization, robotics, AI, and algorithms; attitudes toward automation; the media coverage of automation risks; the extent of the assignment of responsibility in the automation debate; and the responsibility network. The results of this investigation complement previous research that focused on a particular technology, such as AI or robotics, by comparing different technologies in a single framework, which allowed for the identification of similarities and differences among different automation realms.

The findings showed that the amount of media reporting has increased since 1991, particularly since 2015. These findings are in line with international research that suggested that the media coverage of several automation realms was on the rise (Fast & Horvitz, 2017; Ouchchy et al., 2020; Righetti & Carradore, 2019; Sun et al., 2020). Additionally, the Austrian data demonstrated that robotics constantly gained more media attention than automatization, AI, and algorithms. However, the coverage of AI has accelerated significantly, and since 2015, it has almost caught up with the coverage of robotics. Potential reasons for this increase may be the accelerated diffusion of automation technologies, their increasing relevance for society and economics, the growing awareness of their benefits and risks, or, simply, media hype about automation in general and AI in particular.

Regarding the overall tone of reports on automation, the results of the present study are in line with previous research that demonstrated that AI and robotics are portrayed predominantly positively in the media (e.g., Fast & Horvitz, 2017; Garvey & Maskal, 2019; Javaheri et al., 2020). However, the comparison of attitudes toward different technologies in the Austrian media also revealed that algorithms were covered significantly less positively than automatization and robotics.

Around 40% of the news articles analyzed in the present study mentioned automation risks. Among 21 different types of risks, shortcomings of technology, loss of jobs, and ethical concerns were the most frequently addressed by the media. The results of the longitudinal analysis demonstrated that risks have become increasingly present in recent public debate, which was also observed in previous studies that examined media reporting on AI over time (Fast & Horvitz, 2017; Ouchchy et al., 2020). The analysis of Austrian data contributes to the literature, showing that media reports on algorithms have been not only less positive but also more frequently associated with discussions of risk compared with reports on robotics, AI, and automatization. The findings of our study showed that the power of algorithms and their shortcomings, such as bias and in-transparency, have become the subject of critical media coverage.

International research on automation has seldom investigated questions of responsibility. The analysis of the assignment of responsibility in the Austrian media showed that responsibility issues were covered in every seventh article. However, the longitudinal analysis demonstrated that the number and share of responsibility claims had increased in parallel with the growing coverage of automation since 2016. Responsibility claims were (in relative terms) more often made in the context of reporting on algorithms than on other technologies. Particularly in the context of robotics, remarkably less responsibility was assigned.

Finally, the media content analysis explored the network of speakers and assignees of responsibility claims. In the automation debate, responsibility has been assigned mainly to the economy and, with a considerable margin between them, to politics. Additionally, the economy also accounted for the largest share of self-references. The results demonstrated the centrality of economic actors in the Austrian discourse on automation. However, regarding the speakers, the results were not in line with previous studies that found that industry and business stakeholders were predominant in the media coverage of AI (Brennen et al., 2018; Sun et al., 2020). In contrast, the results showed that in Austria, scientific actors had an almost equal say.

Although political actors were often assigned responsibility, they were rarely covered as speakers who expressed responsibility claims. In contrast, scientists often appeared as speakers, but they were rarely called to account. In addition to scientists (Scheufele & Krause, 2019), there were calls for a greater visibility of civil society (e.g., Brennen et al., 2018; Habermas, 1989) in including alternative and independent views of technology in the public debate. Civil society actors, such as critical NGOs, played a subordinate role in the Austrian automation debate, but they had more say than political actors, and they served more often as sources in answering questions about responsibility compared with the British discourse on AI (Brennen et al., 2018). Regarding human and social responsibility, society was called upon to assume responsibility more often than individuals were. Furthermore, journalists were important contributors to the debate. Their high share of responsibility assignment was testimony to their control function in holding to account actors involved (Sarcinelli, 2011).

Although the study was limited to media reporting in one European country, it nevertheless provides insightful findings on the coverage of different automation realms, revealing long-term trends and recent short-term changes. While the overall volume of media coverage has grown, a particularly sharp increase since 2015 was observed. This recent growth was accompanied by increased attention to automation risks and responsibility claims. Moreover, the coverage of risks and responsibilities was correlated with an increasingly negative and critical tone in reporting. Future research could be conducted to determine whether these findings are indicators of the increasing politicization of the automation debate (Allen & Castro, 2017; Chuan et al., 2019; Ouchchy et al., 2020) and a shift from the portrayal of automation as a predominantly technical, innovation, and economic issue toward a social, political, and controversial issue (e.g., Rogers, Dearing, & Chang, 1991, on the agenda-setting process about emerging public issues).

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