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Factors Influencing the Rejection of Automated Journalism: A Systematic Literature Review

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Abstract

Purpose: Automation in journalistic processes is increasingly being discussed in media research and practice. Automated journalism (AJ) enables the fast production of numerous articles in real-time and in various languages. However, given the clear economic benefits of the technology, Automated journalism is only adopted in a minority of newsrooms and has still very limited fields of use. This article aims to contribute to the open question of why AJ is often rejected by professionals in the newsrooms, especially journalists, and which factors are perceived to be crucial for the rejection.

Methodology: A systematic literature review of peer-reviewed journal articles published between 2016 and 2020 was conducted, which identified 40 rejection factors in the research literature. The factors were then analyzed on two dimensions: frequency and intensity.

Findings: The results show that limited bias detection, credibility concerns, and unsolved issues of transparency are perceived as most influential for the rejection of Automated journalism in the newsroom. The study indicated furthermore that soft factors, such as perceived quality or ethical/social issues, are more difficult to overcome than hard factors, such as economic or legal issues.

Keywords: Automated Journalism; Algorithmic Journalism; Systematic Literature Review; Rejection Factor; Influencing Factor; Technology Acceptance Model; TAM3.

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1. Introduction

Journalistic business models are currently undergoing radical transformations. To reduce production costs, improve efficiency and generate new competitive advantages, journalism organizations increasingly use automated processes or algorithmic decision-making (Carlson, 2017; Diakopoulos & Koliska, 2017). Established journalism organizations, such as the Associated Press, the BBC, Forbes, the New York Times, and Los Angeles Times, already use automated journalism (AJ) in text production, translation, placement, and distribution (Graefe, 2016; Graefe & Bohlken, 2020; R. Jones & Jones, 2019; Rojas Torrijos, 2019). In May 2020, Microsoft replaced dozens of journalists with AJ technology in order to select, edit and curate news articles on its homepages

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automatically (Waterson, 2020). Thus, the topic is currently more in need of discussion than ever before.

This article uses the term automated journalism rather than related expressions such as algorithmic journalism or robot journalism. The term is based on the definition by Dörr (2016, p. 3), who states that AJ is 'the (semi)-automated process of natural language generation by the selection of electronic data […] (input), the assignment of the relevance of pre-selected or non-selected data characteristics, the processing and structuring of the relevant data sets to a semantic structure (throughput), and the publishing of the final text on an online or offline platform with a certain reach (output).' This definition was chosen since it covers all stages of the journalistic process that can be supported by algorithms. However, for this study, a relevant refinement to add is that the 'final text' (output) must be a text of journalistic nature.

AJ allows the individualization of content and production of news in different languages – two measures to gain a wider reach. Despite the economic potentials that come with AJ, its adoption rate remains very low (Linden, 2017). Currently, AJ is only used in a minority of newsrooms and has still very limited fields of use, mainly in special segments, such as sports, finance, and weather (Caswell & Dörr, 2018; Dierickx, 2020). It remains an open question why AJ has not been more widely adopted in newsrooms and which factors influence the rejection of AJ technology.

Previous research used slightly more qualitative and exploratory study designs (e.g. Jamil, 2020; Jones & Jones, 2019; Wu et al., 2019b). Multiple studies are concerned with societal and ethical issues (e.g. Dörr & Hollnbuchner, 2017; Lewis et al., 2019; Montal & Reich, 2017), recipients' perceptions (e.g. Graefe et al., 2018; Liu & Wei, 2019; Waddell, 2019) or the technological potential of AJ (e.g. Caswell & Dörr, 2018; Kim & Lee, 2019; Thurman et al., 2017). A few studies have already analyzed the limits of AJ on particular levels. For example, Dörr & Hollnbuchner (2017) discussed the ethical challenges that arise from AJ. Jamil (2020) identified obstacles of AJ for Pakistani journalists. Regarding transparency issues, Diakopoulos & Koliska (2017) identified two overarching factors influencing the rejection of AJ: (1) the concern of overwhelming the audience with too much information and (2) the lack of ethical rules for applying AJ. Leppänen et al. (2020) described which biases could occur in automated news reporting. Other studies addressed the perception of automated news by the audience (Wölker & Powell, 2018; Zheng et al., 2018), the impact of AJ on news credibility (Waddell, 2018, 2019; Wölker & Powell, 2018), and the strategies of journalists in handling the technology (Kim & Kim, 2018; Thurman et al., 2017; Wu et al., 2019a). As Dörr (2016) argued, AJ is able to perform the institutionalized tasks of professional journalism on a technological level. However, the strong dependency on well-structured data and the inability to write interestingly limit the application of this technology. From an economic and organizational point of view, Kim & Kim (2017) investigated why C-level managers decide for or against AJ technology and found that the most relevant concerns are journalists' skeptical attitudes. Journalists believe that consumers will not be receptive to the output and that the technology will not bring immediate economic benefits (Kim & Kim, 2017, 2018).

Despite these findings, automated journalism research lacks a synthesis that reviews the recent research literature, especially concerning the factors influencing the rejection of AJ. The purpose of this article is to fill this gap through systematically surveying peer-reviewed research literature for AJ rejection factors. In contrast to the previous meta-analysis by Graefe & Bohlken (2020), which focuses on the reader's perception of AJ, this study concentrates on the professional's perspective (especially journalists). The Technology Acceptance Model 3 (TAM3) serves as an explanatory framework in order to structure the factors and embed the findings in a theoretical context. Besides providing an overview of the research of the past five years, this review aims to structure and evaluate rejection factors of AJ to contribute to the question of why the technology is not more widely adopted in the newsrooms.

The systematic review is guided by two research questions:

- RQ1: Why is AJ often rejected in the newsroom and which factors are perceived as most relevant in the literature?

- RQ2: How can the factors be integrated into technology acceptance theory?

The paper is organized as follows. First, the choice of the specific theoretical framework for the study from amongst established technology acceptance approaches will be explained. Second, the methodology of literature selection and text analysis will be described. Third, the findings will be presented. Finally, the practical implications of the findings, limitations of the study, and derivations for further research will be discussed.

2. Theoretical Background

The Technology Acceptance Model 3 (TAM3) by Venkatesh & Bala (2008) serves as an explanatory framework in order to structure the factors with respect to the technology acceptance theory (RQ2). TAM3 is well suited to elaborate the Perceived Usefulness and the Perceived Ease of Use of technology – in this case of AJ by professionals. The TAM3 determinants can structure the rejection factors of this study at an empirically tested, theory-based level. The TAM3 is a combination of the TAM2 (Venkatesh & Davis, 2000) and the model of determinants of Perceived Ease of Use (Venkatesh, 2000). As an integrated model, it is adaptable to several technologies. The model is subject to the normative assumption that the employee's behavioral intention affects the user behavior. The behavioral intention is determined by the Perceived Ease of Use and the Perceived Usefulness (see also Figure 2) (Chang & Yang, 2013). There are 11 determinants, which influence the Perceived Ease of Use and the Perceived Usefulness of a technology (Venkatesh & Bala, 2008). Determinants influencing Perceived Ease of Use (e.g. Perception of External Control, Objective Usability) and determinants influencing Perceived Usefulness (e.g. Image, Job Relevance) are clearly delineated from each other. Based on this, the model presents a set of potential (organizational) interventions that could enhance employees' adoption and use of the technology.

Empirical research applies the TAM to different kinds of IT systems, such as E-learning (Al-Gahtani, 2016), cloud computing (Nikolopoulos & Likothanassis, 2018), or mobile commerce (m-commerce) (Raeisi & Meng, 2016). However, it is also applied to digital technologies in the media industry and journalism, such as mobile technologies in journalism (Peko et al., 2020), smart TV (Im et al., 2014), blogging (Chang & Yang, 2013), or political websites (Hong et al., 2015). Peko et al. (2020) found that Perceived Usefulness is highly motivational for journalists in Central Asian media organizations to use mobile technology. TAM can also be applied to understand the technology rejection behavior (Hong et al., 2015). The model provides therefore a useful framework for the theoretical integration of AJ rejection factors.

The Technology Acceptance Models (TAM1/2/3) belong to the most widely applied theoretical models in the field of IT and have been supported by many different researchers with different research purposes, information systems, and methodologies (Lee et al., 2003). Unlike other established innovation and technology adoption approaches, such as UTAUT, TOE, or DOI, the TAM3 is particularly applicable at the professional micro level, in this case especially journalists, but also media managers and data technologists in the newsroom. This literature analysis is insofar centered on the micro-level (professionals in the newsroom). The TAM3 furthermore comprises determinants, which are possible to observe in text material, such as Output Quality, Image, and Objective Usability.

Another aspect that is worth mentioning here is the role of the leader in the technology acceptance process. According to several media management studies, leadership is a central topic for digital transformation (Deslandes, 2016; Küng, 2008, 2017; Londoño-Proaño, 2021), and the application of new technological solutions in media organizations (Tokbaeva, 2018). Leaders directly impact the prowess in implementation, while the control of technology diffusion is mainly seen as a leadership task (Küng, 2017). The TAM3 also refers to the leadership aspect and provides several interventions from the leadership level to prevent technology rejection by employees, such as management support or incentive alignments. The most effective leadership style appears to be transformational (Londoño-Proaño, 2021), which motivates employees to make use of new technology (Tokbaeva, 2018). According to Tokbaeva (2018), technology-driven innovations have a better chance of effective diffusion in news organizations than market-driven projects aiming at organizational or human resource changes. According to this, automated journalism (AJ) seems to have good preconditions to be implemented successfully in media organizations, when the management supports the technological innovation diffusion. Since the adoption rate of AJ is nevertheless quite low in the newsrooms (Linden, 2017), this circumstance will also be reflected linearly to TAM3.

3. Methodology

To survey the research literature, a systematic literature review (SLR) was carried out. The SLR systematically analyses a pre-determined body of research concerning specific parameters (Martin & Assenov, 2012; Petticrew & Roberts, 2006) and is an efficient technique for summarising results and for assessing consistency amongst previous findings (Petticrew & Roberts, 2006, p. 267).

Scopus and EBSCOhost were chosen for this SLR since they are the two largest databases for peer-reviewed scientific literature and cover all relevant publishers (e.g. Elsevier, Taylor & Francis, Sage, IEEE, Wiley, Springer Nature, Emerald), disciplines (e.g. media management, journalism studies, innovation management, and computational studies) and journals (e.g. Digital Journalism, Journalism Practice, Journalism, Media, and Communication) to this study. The search query covered the term automated journalism including common synonymous terms, such as algorithmic or robot journalism. Terms without reference to journalism, such as NLG, NLP, GPT-3, or computational linguistics, were not included in the search query. To answer the research questions, the selected literature also needed to relate to challenges respectively to the adoption or rejection of AJ in the newsroom. The search query was therefore as follows: (‘automated journalism’ OR ‘algorithmic journalism’ OR ‘robot journalism’ OR ‘automated news’) AND (‘adoption’ OR ‘adaptation’ OR ‘rejection’ OR ‘acceptance’ OR ‘implementation’ OR ‘challenge’ OR ‘attitude’) AND (‘newsroom’ OR ‘journalist’ OR ‘professional’). The complete selection process of the literature is shown in Figure 1.

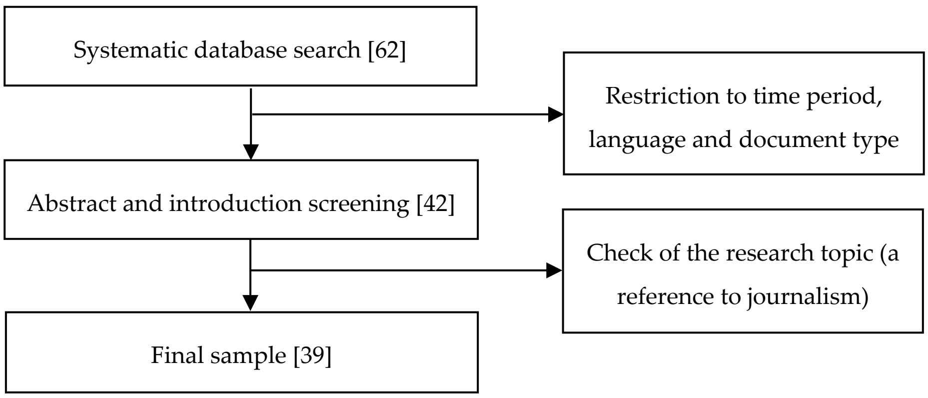

Figure 1. PRISMA Flow Diagram (Moher et al. 2009, adapted by the author).

Due to the topicality and quality of research findings, the search strategy was restricted to publications of the last five years (1/2016–12/2020) and journal articles. It is only since 2016 that a noteworthy number of publications on the topic of AJ adoption in the newsroom have been discernible. Thereafter, publications have increased gradually each year, underscoring AJ adoption's growing relevance. Additionally, results about the obstacles of technology are outdated after a couple of years, since technological abilities grow rapidly. To make generalizable statements about rejection factors, it is also essential that the summarised results meet a consistent and high empirical standard (peer-reviewed journal articles).

Table 1: Coding Scheme of the Intensity Analysis

Strength of Expression	Indicators/Keywords	Anchor Example
1 = very weak	Interviewee/author is very unsure, assumptions, considerations, always with the addition of uncertainty, only one or few known cases Keywords: maybe, possibly, perhaps, might/may/could/should, unsure, uncertain, insecure	'Such friction might be an audience that is averse to automated news.'
2 = weak	Interviewee/author is not really sure, opinions of a single person, claim without conclusion/reasoning, simple assertion, premises Keywords: believe, think, guess, can be, would, probably	'One of the developers explains that […] the output has to be well structured.'
3 = medium	Interviewee/author is quite sure, claim with simple conclusion/reasoning, no addition of uncertainty, some of the interviewees made this experience (not all), one of the (not main but side) findings of a paper Keywords: some, others, often	'Computer stories are comparably shorter. This is because […] computers cannot generate […] information which algorithms cannot access.'
4 = strong	Interviewee/author is sure, made this experience first-hand, most of the interviewees made this experience, one of the main findings of a paper, strong conclusion/reasoning Keywords: strong, surely, certainly, most	'Most studies of innovation […] show that there is a clear drive towards more efficient production processes'
5 = very strong	Interviewee/author is totally sure, made this experience first-hand several times, all of the interviewees made this experience, very strong conclusion/reasoning Keywords: very sure/clear, totally, always, never, obvious, main, first, core	'Algorithms can never become a guardian of democracy and human rights.'

Source: Mayring (2008), adapted by the author.

The final sample comprised 42 articles. All articles were screened by reading the abstracts, keywords, and introductory sections to crosscheck the sample. Articles that addressed journalistic content production with automation software have been included. Articles about chatbots, recommendation systems, or other automated processes in human-computer interaction without any relation to journalism were excluded (3 articles). Appendix A1 shows an overview of the final sample consisting of 39 articles published in 15 different journals.

The analysis of text material as part of the SLR was conducted using a particular qualitative content analysis approach developed by Mayring (2014). This approach allows a researcher to structure qualitative data and to formulate new hypotheses with respect to AJ theory building (Mayring, 2008, p. 20). In the section Theoretical Integration, all identified factors are assigned to TAM3 determinants (RQ2). The use of the TAM3 determinants is essential to create a theory-based category system and to establish construct validity, which is an important quality criterion in content analyses (Mayring, 2014, p. 108).

The sample includes both qualitative and quantitative studies. It was possible to analyze both types of studies due to an integrated coding system based on the work of Jeyaraj et al. (2006) and Mayring (2002). This system combines quantitative and qualitative elements of analysis and enables to code every relevant text passage consistently. First, the entire text material was reviewed, coded, and paraphrased using MAXQDA. The result was an initial list of factors. Second, every single code was evaluated on two dimensions (Mayring, 2008, pp. 15, 57, 90):

- Intensity analysis: This analysis evaluated every code by its strength of expression on a 5-point scale from very weak to very strong (see Table 1). When one factor was coded several times within one article, the strongest expression was chosen.

- Frequency analysis: This analysis addressed the question of how many articles mention one factor.

To extract a more comprehensive list of factors, in the end, factors of the same meaning and context were aggregated (generalization) (Mayring, 2014, p. 69) and groups of factors were formed by topic.

4. Results

4.1. Sample Description

The sample includes 39 articles from 15 peer-reviewed, scientific journals. The content analysis of the sample covers 40 factors characterized by 730 codes. The analyzed studies address, among other aspects, audience perception of automated news (e.g. Graefe et al., 2018; Waddell, 2018; Wölker & Powell, 2018), social/ethical, organizational, and technological issues that have emerged about AJ (e.g. Dörr & Hollnbuchner, 2017; Jones & Jones, 2019; Kim & Lee, 2019).

The studies in the sample represent research on different levels, mainly on the micro-level (user) (e.g. Gonzales & Gonzales, 2020; Guzman, 2019; Jung et al., 2017) and meso level (media organization) (e.g. Kim & Kim, 2017; Wu et al., 2019a, 2019b). The studies tend to use slightly more of a qualitative design, especially interviews (15 articles). Every fourth article has a non-empirical approach such as theoretical discussions. Quantitative methods, such as experiments and surveys, are used in nine articles and five articles use technological analysis.

4.2. Consensual and Opposing Positions about Issues of AJ

When summarising the most consensual positions of the analyzed literature, there is a clear indication that AJ is mainly used in niche segments of newsrooms, such as sports, traffic, weather, and finance (Graefe & Bohlken, 2020; Thurman et al., 2017; Wu et al., 2019a). Furthermore, the production of news using AJ appears to be very dependent on the availability of up-to-date, correct, and complete data sets (Caswell & Dörr, 2018; Linden, 2017; Wu et al., 2019b).

The inability of algorithms to contextualize or to write creatively is mentioned in numerous articles (e.g. Graefe et al., 2018; Kim & Lee, 2019; Thurman et al., 2017; Wu et al., 2019b). These characteristics of AJ, it has been argued, strongly hinder the automated news production process since the outcome is not particularly interesting to read (Kim & Lee, 2019, p. 116; Thurman et al., 2017, p. 1251). Sometimes, the pure data only present 10% of a story; the rest is context, personal conclusions, interpretations, or creative work (Thurman et al., 2017, p. 1247). Nevertheless, the limited ability of AJ to contextualize, to conclude, or to write interestingly has apparently never been the focus of a study.

The fear of journalists that they will lose their jobs due to AJ is omnipresent and one of the main concerns in discussions about implementing AJ (e.g. Guzman, 2019; Jung et al., 2017; Zheng et al., 2018). Although algorithms are still not able to generate real, creative stories (Galily, 2018; Thurman et al., 2017) or to interpret interactions of facts (Caswell, 2019; Wölker & Powell, 2018), many journalists as well as news consumers voice concerns with the possible replacement of journalists by computers (Linden, 2017).

On the other hand, several opposing positions are discussed in the analyzed literature. In terms of transparency, there is no consensus amongst journalists about how to label automated content. The positions range from no labeling at all to a full transparency policy, giving the readers as much information as they can handle (Diakopoulos & Koliska, 2017; Thurman et al., 2017). In sum, the majority of journalists prefer transparent labeling (Thurman et al., 2017).

Bias detection is also perceived very differently in the examined research literature. Some authors argue that AJ has the potential to reduce biases in reporting, while others are concerned that fake news or prejudices may be disseminated quickly (Carlson, 2018; Lewis et al., 2019). Algorithms rarely make simple mechanical errors. Unlike human journalists, however, AJ technology is not able to verify information (Diakopoulos & Koliska, 2017; Jung et al., 2017; Montal & Reich, 2017).

4.3. Rejection Factors and Their Perceived Relevance (RQ1)

The review identified 40 rejection factors, which can be divided into six groups (see Table 2). The numbers in brackets represent index values, formed by the frequency and intensity analysis (see Appendix A2). This additive index indicates the perceived relevance of a factor in the literature.

The first-factor group, output quality issues, such as poorer readability, the inability of the software to write interestingly or to express narrative structure, has the highest group index. Across the literature sample, AJ is perceived as not being able to generate content of the same quality as human-written journalism, and numerous journalists are very concerned about a potential loss of content quality.

The second group, professional issues, deals with workflow matters in the newsroom and the emotional rejection of AJ by journalists. The most relevant factors are the inability of the software to work without human intervention and the omnipresent fear of job instability.

The third group, ethical and social issues, contains all ethical concerns as well as concerns about social consequences (e.g. reliability, credibility, or transparency issues). Due to the essential function of journalism within democracy and society, journalistic content has to comply with high moral standards. Many journalists are skeptical about potential non-compliance with ethical norms and negative social impacts, such as filter bubble effects.

The fourth group, data issues, represents the unavailability of correct, adequate, and complete data sets that are imperative for AJ to generate news articles. The initial assumption was that this group would have the strongest influence on the rejection of AJ technology. More than every second article in the sample mentioned at least one kind of data issue. Thus, this group plays a relevant role in the rejection process of AJ technology; however, it is not perceived as the most decisive one.

Although the implementation of AJ is mainly economically driven (Galily, 2018; Linden, 2017), economic issues are not mentioned very often in the literature. The economic situation of publishers might pave the way for implementing AJ technology in the newsroom. However, issues of reporting quality, ethics, and data requirements primarily drive the rejection of AJ technology. The legal issues comprise two factors: accountability/authority issues and lack of legal regulations for AJ. Although these issues are discussed in more depth in several studies (Díaz-Noci, 2020; Liu & Wei, 2019; Montal & Reich, 2017; Waddell, 2018), this group is the least represented in the literature.

To sum up, *soft* factors, such as perceived output quality as well as ethical/social factors, appear to be more relevant to AJ rejection than *hard* factors, such as professional issues, economic circumstances, and legal obstacles. Soft factors are discussed more often and intensely in the literature. This indicates a predominantly emotional and skeptical position towards AJ. Many journalists report suffering from anxieties and uncertainties about technology and its consequences for journalism in general.

Table 2. Groups of Rejection Factors

Group	Rejection Factors
Output quality issues (278)	• limited bias detection (74) • inability to contextualize, reflect or establish the cause (45) • damaged quality of journalism (40) • inability to recognize public relevance or newsworthiness (35) • inability to write interestingly, creatively, or with humor (32) • poorer readability (30) • challenge to express narrative structure (22)
Professional issues (267)	• inability to work without human intervention (46) • (fear of) job instability for journalists (35) • journalists' attitude (against automated journalism) (32) • technology too inflexible (28) • limited fields of use, mostly special interest content (24) • workload (24) • complexity / usability (18) • difficult to combine with other technologies (18) • lack of journalists' knowledge about data / information patterns (15) • decline of journalists' status in society and the organization (9) • unwanted job assignments (8) • loss of editorial control (7) • lack of collaboration of management, journalists & technologists (3)
Ethical and social issues (228)	• reliability, trust & credibility issue (65) • unsolved issues of transparency (48) • audience's skepticism (20) • 'filter bubble' effect & selectivity (20) • inability to replicate social intelligence or human judgment (19) • lack of morality and ethics (18) • easier to manipulate than human professionals (15) • inability to recognize (cultural) sensitivities (6) • inability to create a public sphere (6) • limited objectivity (6) • information overload (5)
Data issues (94)	• accuracy, completeness, and topicality of data required (39) • unavailability of data (31)
Economic issues (56)	• lack of financial resources & expertise (26) • dependency on well-structured data (24) • doubt of bringing immediate (economical) benefits (13) • alienation of audience/target market (12) • lack of exclusivity, third-party dependency (5)
Legal issues (48)	• accountability/authority issues and data rights (38) • law obstacle (e.g. labor law, lack of regulations) (10)

Note: Numbers in brackets represent index values, indicating the perceived importance of a factor (group) in the literature.

Quantitatively speaking the following factors show the highest index values:

1) limited bias detection (74),

2) reliability, trust & credibility issue (65),

3) unsolved issues of transparency (48).

The most crucial factor, limited bias detection, describes the high likelihood that journalists still find several errors in automated unsupervised content (Leppänen et al., 2020; Upshall, 2018). Jung et al. (2017, p. 297) argue that "[a]lgorithms rely on data and assumptions, both of which are subject to biases and errors". AJ makes exposing biases more difficult (Carlson, 2019), due to complex data models and processing flows, lack of capacity to check every single fact, and a considerably higher output quantity. The second most crucial factor is the reliability, trust & credibility issue. As journalists are professionally obliged to apply bias detection, they are apprehensive about whether they can trust in the credibility and reliability of automatically produced content. For example, Wölker & Powell (2018, p. 2) argue that a lack or absence of credibility "fosters an increasing distrust of the press, which leads to the disruption of journalism".

The third factor, unsolved issues of transparency, is perceived as very crucial for the rejection of AJ as well. There is a challenging discrepancy between not overwhelming the reader with too much information on the one hand, and full disclosure to follow ethical norms, on the other hand (Diakopoulos & Koliska, 2017; Montal & Reich, 2017). Moreover, the opacity of algorithms' decision-making capabilities complicates the discussion about the level of transparency (Diakopoulos & Koliska, 2017).

4.4. Theoretical Integration (RQ2)

The TAM3 serves as an explanatory framework that suggests observable, delineated determinants, which influence Perceived Ease of Use and Perceived Usefulness. These determinants lay the foundation for the theoretical integration of rejection factors. The integration is based on the definitions of determinants by Venkatesh & Bala (2008). Table 3 and Figure 2 show the results of the theoretical integration. In a few cases, one factor can be associated with two determinants. For the sake of clarity, each factor is assigned to the determinant with which it fits best with respect to the determinant's definition by Venkatesh & Bala (2008).

Key determinants, which are perceived to be most influential for the rejection of AJ, are the following:

1) Output Quality (204),

2) Subjective Norm (175),

3) Result Demonstrability (165).

The determinant Output Quality expresses the concern of news professionals that AJ causes a rapid decline in content quality. In the reviewed literature, the Output Quality of AJ is often compared with that of human journalists (e.g. Liu & Wei, 2019; Melin et al., 2018; Thurman et al., 2017; Wu et al., 2019a). The human journalist surely possesses more skills, such as reflection, interpretation, investigation, contextualization, and interesting narration, while AJ is more reliable and faster in producing fact-based content. Overall, however, professionals perceive the issues about Output Quality as very central to the rejection of AJ.

The determinant Subjective Norm encompasses most of the ethical and social issues. According to (Venkatesh & Bala, 2008, p. 277; Wu et al., 2019a), this determinant describes how socially accepted the use of the technology is. Factors such as reliability, trust, and credibility issues or the ease to manipulate the system are perceived as highly crucial for the rejection of AJ.

Result Demonstrability covers two of the three highest-ranked factors (limited bias detection, unsolved issues of transparency). It can be concluded that the lack of demonstrability of AJ, in the form of uncontrollable biases or output accountability, is also very salient for news professionals.

Last but not least, the review indicates that Computer Self-efficacy, Perception of External Control, and Objective Usability are also seen as relevant determinants, while Image, Job Relevance, and Computer Playfulness are hardly presented in the literature.

Table 3. Factor Assignment to TAM3 Determinants

Determinants	Rejection Factors
Subjective Norm (175)	• reliability, trust & credibility issue (65) • audience's skepticism (20) • 'filter bubble' effect & selectivity (20) • inability to replicate social intelligence or human judgment (19) • lack of morality and ethics (18) • easier to manipulate than human professionals (15) • inability to recognize (cultural) sensitivities (6) • inability to create a public sphere (6) • limited objectivity (6)
Image (21)	• alienation of audience/target market (12) • decline of journalists' status in society and in the organization (9)
Job Relevance (62)	• (fear of) job instability for journalists (35) • limited fields of use, mostly special interest content (24) • lack of collaboration of management, journalists & technologists (3)
Output Quality (204)	• inability to contextualize, reflect or establish the cause (45) • damaged quality of journalism (40) • inability to recognize public relevance or newsworthiness (35) • inability to write interestingly, creatively, or with humor (32) • poorer readability (30) • challenge to express narrative structure (22)
Result Demonstrability (165)	• limited bias detection (74) • unsolved issues of transparency (48) • accountability/authority issues and data rights (38) • information overload (5)
Computer Self-efficacy (110)	• inability to work without human intervention (46) • complexity / usability (18) • lack of journalists' knowledge about data / information patterns (15) • difficult to combine with other technologies (18) • doubt of bringing immediate (economical) benefits (13)
Perception of External Control (108)	• accuracy, completeness, and topicality of data required (39) • unavailability of data (31) • lack of financial resources & expertise (26) • loss of editorial control (7) • lack of exclusivity, third-party dependency (5)
Computer Playfulness (24)	• workload (24)
Objective Usability (102)	• journalists' attitude (against automated journalism) (32) • technology too inflexible (28) • dependency on well-structured data (24) • law obstacles (e.g. labor law, lack of regulations) (10) • unwanted job assignments (8)

Note: Numbers in brackets are index values, indicating the perceived importance of a factor (group) in the literature.

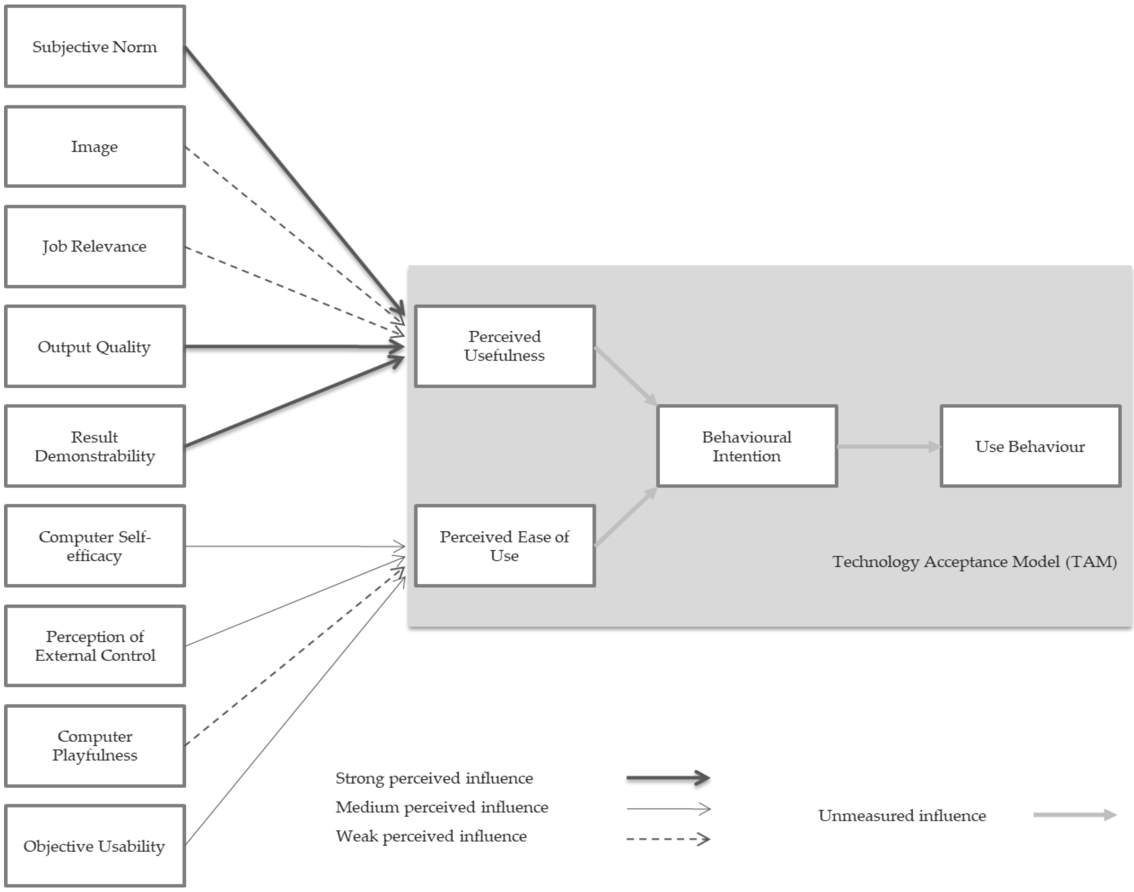

Figure 2. Factor Assignment to TAM3 Determinants. Source: Venkatesh and Bala (2008), adapted by the author. *Note:* For better readability, determinants with an index value = 0 (Computer Anxiety, Perceived Enjoyment) are not illustrated in the figure.

5. Practical Implications

There is a general consensus that journalism organizations do not know where to start or are apprehensive about machine error and job loss (Wu et al., 2019a). Venkatesh & Bala (2008) suggested in TAM3 several interventions linked to single determinants which are able to counteract the rejection of a technology, such as user participation, design characteristics, management support, or incentive alignment. Within the newsroom, these interventions can be supported strategically by the leadership and may contribute to enhancing the acceptance of AJ. In addition, software suppliers could focus on user participation (e.g. elements of interactivity, more flexible templates, and fields of use) or design characteristics (e.g. additional software abilities, machine-learning implementation, usability improvement). High-level media managers can increase the likelihood of a successful implementation, especially by management support or incentive alignment. Management support includes concrete data strategies or emotional support through counteracting journalists' anxiety about job losses. Incentive alignment can happen by motivating journalists to use the software, e.g. by liberating them from boring, repetitive tasks. During and after software implementation, training, organizational support, and peer support can be worthwhile.

6. Discussion and Conclusion

As shown in the result section, the factors limited bias detection, reliability, trust & credibility issues, and unsolved issues of transparency are most present in the literature (RQ1). Generally, editorial challenges are more difficult to overcome than technological ones (Caswell & Dörr, 2018), and emotional barriers are more problematic than rational ones. The review indicates that these soft factors, such as the quality of the output and ethical issues, are perceived as more challenging than the hard factors, such as data issues, economic or legal conditions. The economic situation of publishers might pave the way for implementing AJ. Issues with output quality, ethics, or shifts in professional workflows, however, drive the rejection of the technology. This is accompanied by the theoretical integration which shows that determinants of Perceived Usefulness, especially Output Quality, Subjective Norm, and Result Demonstrability, are perceived to be crucial in the research literature (RQ2). This finding is congruent with the results by Peko et al. (2020), who concluded that Perceived Usefulness is highly motivational for journalists in Central Asia to use new technology (in this case: mobile technology).

The presented findings need to be discussed in light of the limitations of the chosen method. The combination of frequency and intensity analysis helps to evaluate the impact of determinants quantitatively. This additive index indicates how the factor is perceived in the literature. However, the empirically evident, objective relevance cannot be evaluated with this method. Shifts may occur due to trends in research or the special priorities of an author. This form of bias could be reduced via the intensity analysis coding scheme (Table 1), which ranks assumptions and opinions less important. Additionally, every factor was evaluated in the context of the whole text passage and the conclusions, which the text drew.

In general, factor names are primarily based on the authors' wording and descriptions of factors in the text material (paraphrasing). The authors sometimes use very narrow and detailed descriptions (e.g. lack of collaboration of management, journalists, and technologists); other times, they mention a factor on a broader level (e.g. accountability/authority issues and data rights). As broader factors attain higher factor indices than narrow factors, not all factors are comparable on the same level. In order to reduce this bias, the factors are assigned to determinants of TAM3 that are theoretically pre-defined and therefore easier to compare on a higher, more general level. This leads to a broader and more usable category system (Mayring, 2008, p. 115).

According to the possible biases, the rejection factors studied here may differ in their diversity from those in reality. Due to the variety of rejection factors extracted from the text material, it is apparent that every researcher and news professional has a different view on AJ. Therefore, it is likely that the diversity of rejection factors in reality is constantly changing.

Despite these limitations, the presented findings provide relevant insights about factors influencing the rejection of AJ in newsrooms. The determinants of TAM3 can be easily adapted to AJ. In future research, it will be important to corroborate the findings with quantitative methods to strengthen the empirical evidence. Additionally, interventions related to the key determinants need to be investigated. The substantiation or extension of results by using quantitative methods would be a worthwhile endeavor.

In order to support journalism in becoming more interconnected with AJ software and other technological tools, processes, and ways of thinking, it is necessary to consider the full array of actors, audiences, and activities in cross-media news work and investigate how they might intersect (Jones & Jones, 2019; Lewis & Westlund, 2015). The results presented here can function as a guideline for success factor research and technology acceptance/rejection in journalism studies in an interconnected media environment. The determinants, as well as the interventions of TAM3, can be easily adapted to AJ and its factors. Future research needs to empirically substantiate the determinants, interventions, and factors with quantitative methods. In addition, the applicability of specific factors and groups could further be tested for other technologies supporting value creation processes in journalism organizations.

To give an outlook, it remains conceivable that publishers, beyond the American big media players, will automate more and more editorial processes in the future. The results of this study confirm the initial statement that a multitude of relevant challenges arise with the arrival of automation in newsrooms. The resultant reluctance of publishers and the low adoption rate is therefore understandably justified. First, the most important rejection factor, limited bias detection, would have to be significantly improved before acceptance and trust in the technology can grow. This would be a first step before the economic potential of AJ (e.g. far greater reach, news production in real-time, higher outcome rate) can be exploited.

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Appendix A1

Final sample: 39 peer-reviewed articles (2016-2020) from 15 scientific journals

- Blankespoor, E., deHaan, E., & Zhu, C. (2018). Capital market effects of media synthesis and dissemination: Evidence from robo-journalism. Review of Accounting Studies, 23(1), 1–36. https://doi.org/10.1007/s11142-017-9422-2
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Appendix A2

Example Matrix - Calculation of Additive Factor Indices

	Factor 1	Factor 2	Factor 3	*Intensity of Expression*
Article 1			1	*1 = very weak*
Article 2		4		*2 = weak*
Article 3	2	3	5	*3 = medium*
Article 4			4	*4 = strong*
Index ∑ intensity values per factor	**2**	**7**	**10**	*5 = very strong*

Biography:

Meike V. Grimme is a doctoral candidate in Media Management at the University of Hohenheim and the University of Applied Sciences, Cologne, as well as a PhD scholarship holder of the State Graduate Funding Baden-Württemberg, Germany. She has earned her M.Sc. in Communication Management and studied among others at the UC Berkeley and the University of Padova. Her research interests include Technology Adoption in Media Organisations, Digital Journalism Studies, Media Business Model Innovation and Communication & Marketing Strategy.