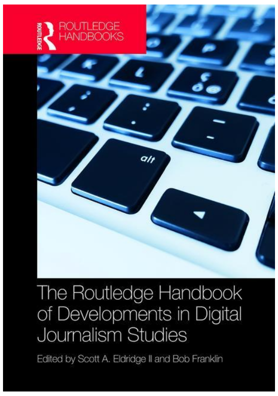

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Disclose, Decode, and Demystify

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DISCLOSE, DECODE, AND DEMYSTIFY

An empirical guide to algorithmic transparency

Michael Koliska and Nicholas Diakopoulos

Scholars and educational and professional organizations of journalism have embraced transparency as a new critical norm guiding journalistic practice (Deuze, 2005; Allen, 2008; McBride and Rosenstiel, 2014; SPJ, 2014; RTDNA, 2015). The rise of transparency to a new journalistic core value has been fueled by digital technologies and the belief that transparency may counter the loss in credibility and trust (Kovach and Rosenstiel, 2014; Hayes et al., 2007; Plaisance, 2007) the news media has experienced in the recent past (Pew Center, 2012).

The primary tenet of transparency is that it enables audiences to learn more of how news is produced but also about individual journalists and news outlets. Deuze (2005: 455) defines transparency as the "ways in which people both inside and external to journalism are given a chance to monitor, check, criticize and even intervene in the journalistic process." However, the increasing implementation of computational journalism[1] and use of algorithms in news production, curation, and dissemination (Diakopoulos, 2016) challenge the new norm of transparency due to the opacity in algorithmic automated decision making (Diakopoulos, 2015).

Computational or algorithmic journalism is increasingly becoming part of the daily news production and news consumption of crime and sports stories, earning reports, and more (Graefe, 2016; see also Montal and Reich, this volume, Chapter 4). Writing software employed by the likes of the Associated Press (AP) and Yahoo can churn out thousands of stories. Currently the focus is primarily on sports, financial, and political stories (AP, 2015; Yahoo, n.d.), but algorithms have also been used to report on earthquakes (Oremus, 2014), generate event-driven narratives around things like car chases (Caswell and Dörr, 2017), or write and post entries to *The Los Angeles Times* homicide blog (Young and Hermida, 2015).

The application of computational journalism goes beyond the creation and writing of news stories. In the news media algorithms are also being used to simulate and predict possible outcomes based on vast amounts of data. News organizations such as the *New York Times*, BuzzFeed, and Mashable use algorithms to select and distribute stories suitable for social media (Wang, 2015; Nguyen et al., 2015; Albeanu, 2015). In order to cope with the issues of scale, due to ever growing amounts of data, news production processes make increasing use of algorithmic tools to find, verify, and filter sources, while also disseminating content via news bots on social media (Park et al., 2016; Thurman et al., 2016; Lokot and Diakopoulos, 2016).

The opaqueness that comes with algorithmic news media work finds its counterbalance in algorithmic transparency, which we define as *the disclosure of information about algorithms to enable* *monitoring, checking, criticism, or intervention by interested parties.* The values, practices, and standards for algorithmic transparency are still developing, especially regarding questions of how and when information concerning algorithms can and should be disclosed. Initial attempts focused on explaining the methods of data-driven stories (see ProPublica; Grochowski Jones and Ornstein, 2016) or occasionally providing open-source code and data on repository sites such as Github (see BuzzFeed, FiveThirtyEight). Other efforts to inform the public about the various technologies and algorithms used in news production have taken on the forms of academic papers, as in the case of the BBC (Shearer et al., 2014) or blogs (see "Open" on the *New York Times* website).

While transparency is just one specific effort toward greater accountability of algorithms in the news media (Dörr and Hollnbuchner, 2017), it's a notion that has gained greater purchase within journalism and society at large (Schudson, 2015). Hence this research explores the question: How exactly might the news media become transparent about the algorithms it uses in news production? The underlying goal of this study is to develop a transparency or disclosure spectrum that allows professional journalists to swiftly and effectively consider options of information disclosure concerning algorithms within a specific institutional context. For this purpose we examined the discussions of nine focus groups that included members from national news outlets and universities in the US.

Our findings suggest various information disclosure opportunities about algorithms across four areas: data, model, inference, and interface. Additionally, results show that despite the automated nature of algorithms, the human factor and human decision making are critical factors in the consideration of transparency.

Transparency

Transparency and the news media

The field of journalism increasingly acknowledges transparency as an important norm for today's journalism (Vos and Craft, 2016). The *New York Times* public editor Liz Spayd (2016) for instance, suggested that audiences "want more transparency in stories that are shapeshifting before their eyes". This is because transparency is deemed to help to "discover social truth" and "the truth about the manufacturing of news", while also "increasing legitimacy with citizens" (Allen, 2008: 324).

In the research literature, journalistic transparency is frequently discussed as an ethical imperative (Plaisance, 2007) and as a way to increase legitimacy (Allen, 2008; Karlsson, 2010) and credibility in the news media (Hayes et al., 2007). This is because the opening up process that transparency enables "gives the public a basis on which to judge whether a particular kind of journalism is the kind they wish to encourage and trust" (Kovach and Rosenstiel, 2014: 291). Supporters of the concept consider transparency "the new objectivity" (Weinberger, 2009), a better form of truthtelling (Singer, 2007), and a means to showcase that professional journalism is superior to nonprofessional content (Karlsson, 2011).

The notion of transparency is also related to corrections, as the show of vulnerability by admitting failure is deemed to build trust (Silverman, 2013). Yet critics of this type of transparency such as Broersma (2013) suggest that the journalistic institution may lose legitimacy, as the admittance of fallibility would undermine the authority of journalism. Some research shows that transparency about corrections may actually have limited effects and does not necessarily lead to more credibility or further journalistic authority (Karlsson et al., 2017). Overall, research still has to find whether transparency will indeed affect news audiences' credibility perceptions (Karlsson et al., 2014; Roberts, 2007; Tandoc and Thomas, 2017).

The academic and institutional discourse concerning transparency suggests that transparency has become critical and a core value for journalism, yet research has also shown that journalists are still struggling to adopt transparency in their daily work (Chadha and Koliska, 2014; Koliska and Chadha, 2017) or favor objectivity as a core journalistic norm (Hellmueller et al., 2013). Nevertheless, journalism is also being influenced by open-source culture, creating a fertile ground for more transparency such as open data and public involvement in news production (Coddington, 2015; Lewis and Usher, 2013).

Algorithmic transparency

The growing use of algorithms in all aspects of news production and distribution allows for faster and more effective work processes, yet at the same time this new efficiency based on difficult to parse automated processes runs counter to the notion of transparency and automated technologies (Diakopoulos, 2015). A major issue regarding algorithmic systems is the possibility of subtle biases (Friedman and Nissenbaum, 1996) which can influence information analysis and the understanding of issues that various publics may rally around (Gillespie, 2014). Algorithmic transparency in the news is then the idea to publicly show and reveal the workings of computational systems in order for users to discern the embedded values of specific algorithms, which would allow a better understanding of journalism with a specific point of view (McBride and Rosenstiel, 2014). Research shows that some forms of algorithmic transparency such as information disclosure and explanations of algorithmic systems can positively affect user perceptions. Cramer et al. (2008) showed that explanations about a specific recommender algorithm can positively influence the acceptance of particular recommendations. Kizilcec (2016) indicated that transparency can indeed increase trust when used in an information seeking context. But additional information provided through transparency can also diminish the user experience (Schaffer et al., 2015). Other studies have also explored information disclosure in personalization (El-Arini et al., 2012) and ranking (Diakopoulos et al., 2014).

Exploring algorithmic transparency in the media

This exploratory study is an attempt to move research and practice of algorithmic transparency toward a more common ground that is applicable to a wide range of automated applications in the news media. Fifty participants across nine focus groups discussed the scope of information disclosure about algorithms including aspects such as feasibility, benefits, and limitations. In order to inform transparency practice and guide research we asked:

RQ1: What elements of algorithms could be made public?
RQ2: What are the limitations of algorithmic transparency?;
RQ3: What are possible comprehensive disclosure mechanisms for algorithmic transparency?

Methodology

We conducted focus groups to collect a wide variety of perspectives, perceptions, and practices (Puchta and Potter, 2004) and to stimulate interactivity to evoke group insights (Morgan, 1996). The issue of algorithmic transparency can be considered a highly specialized subject matter, and as such we invited participants with a similar professional background to elicit expert evaluations (Kemper et al., 2003).

Participants

Focus group participants comprised of academic and industry specialists on algorithmic applications from the fields of journalism and computer sciences. Academic participants came from North American universities such as Columbia, Stanford, NYU, Northeastern, Rutgers, CUNY, University of Maryland, Harvard, Princeton, and others. Industry practitioners included editors and reporters from the *New York Times*, *Washington Post*, *Texas Tribune*, NPR, *Boston Globe*, Associated Press, etc., but also data scientists and managers with companies such as CNN, Mashable, Vocativ, SmartNews, Chartbeat, and Bloomberg.

Case studies – stimuli

The basis for focus group discussions were three case studies (CS) specifically developed to mirror current use of algorithms in content creation (CS1), content curation (CS2), and simulation, prediction and modeling in storytelling (CS3). CS1 addressed the implementation of natural language generation software to write content (e.g., Automated Insights and Narrative Science). CS2 dealt with filtering algorithms that curate, rank, and recommend or personalize content akin to the Facebook newsfeed. The third case study's (CS3) emphasis was on simulation in news stories such as political predictions and models for data visualization. All case studies were explained (including relevant technological aspects) and shared before as well as during the discussions.

Procedure

The fifty participants were randomly assigned to three focus groups of 14–18 participants, as larger groups are deemed to elicit a wider range of responses (Morgan, 1996). Three different moderators led and facilitated each group discussion. Each focus group discussed the individual case studies for about an hour. Groups were mixed randomly again after each session so that everyone participated in each case study once.

As moderators guided and prompted the discussion about algorithmic transparency, participants collectively gathered, categorized, and displayed possible avenues for information disclosure. In a second step, pros and cons of disclosing information about algorithms such as manipulation and costs were discussed. All participants were debriefed at the end as one large group.

Stenographers transcribed each discussion in real time, excluding any identifying information of the participants. We then analyzed all transcripts employing open iterative coding including affinity diagramming, typologizing, and memoing (Lofland and Lofland, 1994). A codebook was created and applied to all transcripts after coding five case study transcripts independently resolving any inconsistencies.

Study findings

The focus group discussion analysis of the three case studies provided us with an empirically grounded typology covering a broad spectrum of information disclosure for various algorithms. A central theme that emerged from our typology is the human factor that is deeply embedded in algorithmic systems. Several focus group participants acknowledged that the underlying human involvement in the creation, design, and decision making of algorithms needs to be parsed out and disclosed. Specifically, a participant suggested that "when we're talking about algorithmic accountability, we also want to elucidate the human accountability that is going on inside newsrooms in order to make the public trust newsrooms more" (CS2).

Table 19.1 Summary of transparency factors across four layers of algorithmic systems

Layer	*Factors*
Data	• Information quality ◦ Accuracy ◦ Uncertainty (e.g., error margins) ◦ Timeliness ◦ Completeness ◦ Sampling method • Definitions of variables • Provenance (e.g., sources, public or private) • Volume of training data used in machine learning • Assumptions of data collection • Inclusion of personally identifiable information
Model	• Input variables and features • Target variable(s) for optimization • Feature weightings • Name or type of model • Software modeling tools used • Source code or pseudo-code • Ongoing human influence and updates • Thresholds or other embedded rules
Inference	• Existence and types of inferences made • Benchmarks for accuracy • Error analysis (including, e.g., remediation standards) • Confidence values or other uncertainty information
Interface	• Algorithmic presence signal • On/off • Tweakability of inputs, weights

We categorized findings according to the notion of a data pipeline, which organizes our typology into four phases of an input-output framework. Following the flow of information toward the end user, we distinguish between: data (inputs), model (transformation), inference (output), and interface (output). In Table 19.1 we detail and discuss the relevant information types for disclosure of human-algorithm systems that emerged during the focus group discussions.

Humans and algorithms

The disclosure of human involvement in algorithmic systems is critical to mapping the affordances of algorithmic transparency, especially because human actions are like "a black box" and much "harder to be objective with" than parameters of an algorithm (CS1). Focus group participants suggested that human actions could be disclosed through editorial explanations concerning the selection or optimization of data and use of algorithms but also by identifying the authors, managers, or designers of algorithmic systems. One critical aspect mentioned was the determination of credibility of automatically generated news content (CS1), which could be enhanced by indicating the existence of a human editor through a byline. As algorithmic systems are the result of collaborative work, such labeling efforts may be problematized (Nissenbaum, 1996) even though they could contribute to normative and institutionalized standards that are still in flux (Montal and Reich, 2016, and this volume, Chapter 4).

The acquisition of software can further complicate disclosure practices, yet participants suggested making aspects like configuration and parameterization of such off-the-shelf software transparent. Some aspects considered for disclosure were much more ephemeral and difficult to parse out, like the social-cultural context or chronological history that influenced the development of an algorithm. Other more concrete aspects that could shed light on the human involvement in algorithmic use and production included naming the developers of an algorithm and explaining their rationale and assumptions but also disclosing who supervises algorithmic performances and how, or as a participant pithily stated, "who is behind it all" (CS2).

The multiple levels of human involvement in algorithmic systems reflect the obstacles of parsing out human influences. Participants thus considered the notion of simply disclosing the presence of an algorithm in the first place. In particular, discussions around the automatic generation of news content (CS1) triggered deeper considerations of making human involvement transparent. One participant outlined the scope of the issue:

> I think it is very interesting [. . .] why there is still this split between an algorithmically generated piece and a human-generated piece. The human-generated piece ends up having to be accountable. I could fire that person. There is an incentive to do a reasonable job. A machine is engineered to be as good as it can be. When you scale it up to hundreds of thousands or millions of pieces and there is some margin of error and at some time it will screw up – it could potentially be a real problem [CS1].

Another participant summarized, "there is a worry you cannot correct for this systematic error" (CS1), as the processes of implementing improvement can be much more complicated for algorithmic systems.

Input-output pipeline

As algorithms can be part of various processes in the production, curation, and/or management of information, we focus on the input-output pipeline as a model to describe critical phases of automated systems. The pipeline starts with the 'data' or information that is fed into a system then transformed by a 'model' and put out as an "inference" or classification, which is presented to the user through an "interface." Based on this pipeline, we describe in the following subsections the various avenues of potential information disclosure around algorithms.

Data

Data is the most basic and crucial element for any type of algorithmic system including such processes as machine learning, simulation, personalization, and automatically generated content. Focus group participants repeatedly discussed ways of disclosing information concerning the quality and validity of data. The core aspects of data quality that emerged were accuracy, uncertainty (e.g., error margins), and completeness or missing elements. With respect to validity, participants suggested factors such as timeliness (i.e., when data was collected), provenance (e.g. sources), sampling method, and inherent assumptions or limitations in the data collection but also data transformation, vetting, cleaning, or editing. Participants suggested disclosing the data with annotated descriptions including a reference if human involvement was present in these processes. Metadata was identified as a vital element for such information, possibly shedding light on private or public sources or identifying information. Focus group participants were specifically interested in learning how data profiles based on user activity influence algorithmic performance: "These would be aspects of the profile of users or type of personal information used and how the algorithm is tested, how the algorithm ranks stories based on traffic, different inputs and variables" (CS2). Such information, a participant suggested, could also be used to correct personal data, ultimately improving algorithmic performance.

The underlying principles of algorithmic systems, even though they operate on a quantified simplification of the world, are human-made definitions and rules. The human influences on the selection and processing of data are thus vital elements of any transparency information around algorithmic systems.

Model

The model of an algorithmic system, which can be understood as a simplified or abstracted version of reality, was seen as a critical element for algorithmic transparency. Participants indicated that understanding the methodology and the modeling process would be vital to discern an algorithm's process of prediction, classification, ranking, or association. Specifically, discussants were interested in the type of model (e.g., linear, nonlinear, etc.), what is being optimized by the model, how different variables are weighted, and what assumptions or limitations may be embedded in software modeling tools. Similarly, transparency of data used to train a model could offer critical insights concerning the optimization and machine learning features of algorithmic systems. Some participants interpreted these aspects as editorial factors since specific parameters in the model not only determine the semantics but also the interpretation of the data. In automatically generated news stories, for instance, it was pointed out that understanding thresholds could be critical for end users to see how a value is interpreted, e.g., as "moderate" versus "extreme."

Several participants said they want to see the source code because

> if I have the data and the models I can put everything in a website, somebody can come and say your regression model is wrong. So you can have discussion based on hard facts, meaning you have the code and data. [CS3]

Disclosing the code and its various revised reiterations allows tracing the modeling process from input to output, yet several participants also pointed out that the code may be too technical for the average user.

Focus group discussions again acknowledged human involvement and rationales in algorithmic modeling and decision-making processes, pointing toward aspects like organizational culture that influences aspects like weighting, exclusion-inclusion of variables, and also the evolution of models. For instance, a participant asked: "How are election models learning from the previous elections process?" (CS2). Several discussants saw parsing the human decision-making processes from algorithmic optimizations as a challenge for algorithmic transparency. Yet two approaches emerged: (1) disclosing human decisions or editorial choices influencing the modeling and (2) disclosing how those choices are applied in the code. Such forms of transparency could allow end users to better gauge a news organization's culture and social context.

Inference

The issue of algorithmic output inferences was frequently addressed with questions concerning uncertainty and accuracy. Discussants deemed that learning more about output inferences of an algorithm such as classifications, predictions, or recommendations would provide significant insights to better understand algorithmic systems. In particular, participants wanted to know how outliers and 'normal' cases would be handled in the various inferences. Such information, it was pointed out, would allow a better understanding of embedded assumptions in an algorithm:

"People get all fancy about their underlying statistical model and the mathematical assumptions in some algorithm, and they forget to account for those assumptions when drawing conclusions" (CS3). In the case of Facebook, participants suggested that algorithms often assume relations and preferences of users, and thus they suggested that disclosure concerning inference should both include accuracy but also what inferences are being made to begin with.

Study participants proposed to include not simply a summary of statistics but also specific details such as confidence values or "standard deviation [to show] how precise these results are" (CS3). Disclosing aspects of uncertainty and error including sources (human, data, algorithm) would help users to understand the scope of inferences including possible underlying assumptions. Such forms of transparency, participants suggested, should be accompanied by contextualizing descriptions of the various aspects of uncertainty and how those relate to the overall inference process.

Interface

The last stage of the input-output pipeline – the interface – directly interacts with end users to provide transparency information in a comprehensive form. Participants offered a wide range of ways to present transparency information about data, model, and inferences, from FAQs to periodic transparency reports, possibly by ombudspeople. At its most basic form it was suggested to simply signal the user via an icon on the interface level that the content has been, for instance, personalized by an algorithm. Or as a participant put it, "I wonder if any time you receive information that had been curated by an algorithm, that there was some visual cue like 'algorithm at work'" (CS2).

Interactivity was seen by participants as an ideal way to explore transparency information but also seen as a possible limitation depending on "whether or not the designer has exposed certain things for you to play with" (CS2). Discussants suggested allowing users to access data for sports stories such as box scores or providing an editorial explanation. Participants also asked "how can the user control the algorithm" (CS2) and proposed that interactivity could help to learn more about an automated system:

> You could click on the forecast and see how uncertain it was and how it changes but you could even expand this model by giving people the possibility to, for example, play different economic indicators and see how they would affect the forecast [CS3].

In the same vein, some focus group members suggested an on/off switch for algorithms to "know when I'm in a personalized space or not" (CS2). Such forms of algorithmic manipulation including the alteration of parameters would allow for a direct comparison of the algorithm's impact on content.

An unintended side effect of transparency or disclosure of information on the interface layer is the possibility of information overload. Some focus group participants voiced concerns that transparency efforts may hamper the attempt at making algorithmic systems more discernable for the average user. In that respect several discussants suggested that difficult to access technical information should be translated "for people to actually get it intuitively and easily" (CS2). Nevertheless, other participants warned that such "translations" could lead to imprecisions and wrong conclusions regarding the algorithmic systems and their underlying assumptions.

A number of focus group discussants saw algorithmic transparency in itself as impractical and asked if users would indeed want such information. One participant even suggested that describing an "extremely detailed model [could] actually turn off the public" (CS3). And some wondered whether algorithmic transparency is a self-serving effort by media outlets: "The organization is happy, but do nonspecialists care?" (CS1), while others argued that the audience has changed and in fact "wants transparency now" (CS1). The concerns regarding algorithmic transparency are indeed problematic, as primarily experts but not necessarily the general public are able to comprehend intricate technical information. Thus balancing the various information needs of users while at the same time avoiding information overload or diminishing the user experience remain a practical and theoretical challenges.

Consequences and challenges to algorithmic transparency

As a final step of the focus group discussions about avenues for algorithmic transparency, participants were asked to gauge the various disclosure options according to aspects such as feasibility, manipulation, or general organizational costs. In fact, business considerations featured as the most prevalent moderators for algorithmic transparency. Participants pointed toward a higher workload to produce transparency information, which would result in higher costs when preparing source code, editorial explanations, and data. On the other hand, it was suggested that algorithmic transparency "might be technically very easy to do, but then in terms of the news organization's self-interest, particularly from management and from a financial perspective, it might be costly" (CS2). At the same time, discussions around feasibility and costs showed that financial or organizational benefits for greater transparency were difficult to assess, and, as such, participants struggled to propose concrete incentives to be more transparent.

Focus group discussants also saw pitfalls of transparency with respect to legal and privacy concerns when, for instance, data was not sufficiently anonymized or errors were made. "If we published something inaccurate [. . .] to say so publicly might be admitting in some jurisdictions an amount of guilt, like for something that we could be sued about" (CS2). Moreover, there was also doubt whether disclosing uncertainty information such as error rates would undermine the validity of an article, as users may come to see the entire content as faulty.

Another issue hampering algorithmic transparency involves proprietary concerns, since disclosing source code could mean losing a competitive advantage or possibly opening a system up to manipulation via feedback loops into the algorithm. At the same time, some organizations may not be able to be as transparent as they might like "because the news organizations that are buying [software/algorithms] can't produce the codes" (CS2).

Even though participants did not provide clear incentives for organizations to implement transparency, several discussants suggested that disclosure practices would improve perceptions of credibility, reputation, and legitimacy. One participant argued that disclosing information about algorithms is not necessarily about evaluating information, but "you kind of evaluate trust" (CS1). Nevertheless, such beliefs were also met with questions like: "Do you think it would seriously impact your credibility?" (CS3).

Generally, participants considered algorithmic transparency as a way to hold news organizations accountable. But they also recognized the strategic incentives for organizations to signal greater transparency in order to increase legitimacy, while possibly withholding information that could undermine the reputation of an organization.

Discussion and conclusion

The findings of this focus group study offer a variety of avenues for transparency of algorithmic systems along the input-output pipeline. As transparency is increasingly becoming a core concept for journalistic accountability and journalistic truth telling, the discovery and recommendation of feasible transparency practices is critical for improving journalism's credibility and legitimacy.

Yet at the same time our results indicate two factors that may hinder the implementation of transparency: (1) lack of business incentives and (2) information overload for users.

This empirical study echoes theoretical considerations around the ethics of algorithmic journalism including data and code transparency (see Dörr, 2016; Dörr and Hollnbuchner, 2017; Dörr, this volume, Chapter 23). Our findings also expand recently proposed ethical frameworks around algorithms (see Ananny, 2016) by explicitly stressing the role of human involvement in the production of algorithmic systems. While Neyland (2015) made first inroads through ethnographic techniques underlining the dynamic human design processes in developing algorithmic systems, it remains a challenge for future studies to separate human and algorithmic decision processes while also acknowledging the intrinsic hybridity of such automated systems.

We argue that the various factors of disclosure this study proposes (see Table 19.1) are critical for an emerging standard of algorithmic transparency, which may be quintessential for increasing institutional legitimacy. An algorithmic transparency standard would then work twofold. On the one hand it could inform use and design of algorithms within the news media industry, and on the other it would allow institutional members and the public to hold organizations accountable. The institutional implications of furthering algorithmic transparency may not become apparent in the short term, as adopting, practicing, and integrating transparency into everyday journalism should be considered a longitudinal process. Time is a critical factor in the adoption and dissemination of innovations (Rogers, 2003) such as algorithmic transparency.

The consideration of time may be especially critical when considering that many new media platforms have been built on different foundations in comparison to traditional media, because such new media platforms often focus or build their value systems around the end user experience (Ananny and Crawford, 2015), frequently neglecting issues of greater public interest such as diversity and accountability including transparency (Napoli, 2015). Our analysis of focus group discussions suggest a similar trend, as participants frequently pointed out that transparency information may diminish the user experience. The difference in institutional orientation indicates that new media platforms may have a more pragmatic and customer-oriented outlook rather than an ethical outlook, which in turn raises questions regarding such organizations' willingness to be increasingly transparent in the first place, especially as no proven business incentives seem to currently exist (Fengler and Russ-Mohl, 2014; Saurwein et al., 2015). Yet a changing audience that expects more transparency (McBride and Rosenstiel, 2014) could be a trigger for more disclosure in the future. Transparency may then be understood not simply as an ethical principle but as a viable avenue to enhance the user experience (Diakopoulos et al., 2014).

While the focus on user experience could ultimately lead to greater transparency, there is a much more urgent need to bolster institutional values, perceptions, and practices of media work in general and journalism in particular. The adoption of isomorphic practices and values can increase institutional legitimacy (DiMaggio and Powell, 1983). In a primarily digital media environment that allows, voluntarily and involuntarily, for more disclosure about the journalistic production and producers, such isomorphic practices include transparency as a path toward greater media accountability. In order to strengthen the institutional standing of media organizations, institutional members need to adopt and implement transparency practices in their daily work (Meyer and Rowan, 1977), creating an impetus to be more transparent despite concerns about the user experience. Such disclosure practices may include ombudspeople's periodic transparency reports, editorial explanation, disclosure of source code, error analysis, or the methodology of data collection and processing. Such practices do not only hold media organizations accountable but also form and uphold an institutional culture of transparency and accountability. In fact, a survey among journalists found that upholding organizational or editorial guidelines (59%) and institutional or professional codes of ethics (50%) can impact journalistic behavior the most (Powell and Jempson, 2014).

Normatively speaking, transparency around algorithms is of vital importance even if there are practical concerns such as information overload. Many users may not care on a daily basis about the methodology of algorithmic systems or the quality of the data. But the news media serves a broad public, of which some concerned users may value expert accounts and explanations (Tilly, 2006). Thus in order to satisfy the various information needs of users – from general users to experts – we propose a multi-layered 'pyramid' model of transparency. This pyramid starts at the tip with a hint or an opening to transparency information at the user-interface level. Users could then work their way down to gradually more detailed levels of explanations of the system and content production processes. Such an approach could decrease the danger of information overload by offering increasingly more data from one level to the next.

While our framework for this study – based on three case studies – is not exhaustive in regard to the use of algorithms in news systems, we believe that this study's pragmatic approach will offer a basis for an algorithmic transparency standard that can be built upon in future research. In summary, this research makes clear that algorithmic transparency requires the consideration of multiple stakeholder perspectives, including organizational incentives and costs, end user tasks and utility, and ethical practices.

Further readings

To see various demonstrations of the practical application of the transparency model presented in this chapter see "Enabling Accountability of Algorithmic Media: Transparency as a Constructive and Critical Lens" by Nicholas Diakopoulos. A healthy critical examination of transparency and its various shortcomings is presented by Mike Ananny and Kate Crawford in "Seeing Without Knowing: Limitations of the Transparency Ideal and Its Application to Algorithmic Accountability". Finally, for a more general treatment of ethical implications regarding the use of algorithms throughout various aspects of society, see "The Ethics of Algorithms: Mapping the Debate" by Brent Mittelstadt and colleagues. To keep on top of the state-of-the-art in *how* to be transparent about algorithms, the Fairness, Accountability, and Transparency in Machine Learning (FATML) workshop is an excellent venue: www.fatml.org.

Note

1 The notion of computational journalism or "algorithmic journalism" (Dörr, 2016) refers to finding, telling, and disseminating news stories with or by algorithms.

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