Digital Literacy and Online Political Behavior*

Andrew M. Guess† and Kevin Munger‡

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Abstract

Digital literacy is receiving increased scholarly attention as a potential explanatory factor in the spread of misinformation and other online pathologies. As a concept, however, it remains surprisingly elusive, with little consensus on definitions or measures. We provide a digital literacy framework for political scientists and test survey items to measure it with an application to online information retrieval tasks. There exists substantial variation in levels of digital literacy in the population, which we show is correlated with age and could confound observed relationships. However, this is obscured by researchers' reliance on online convenience samples that select for people with computer and internet skills. We discuss the implications of these measurement and sample selection considerations for effect heterogeneity in studies of online political behavior.

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†Assistant Professor, Department of Politics and School of Public and International Affairs, Princeton University. Email: aguess@princeton.edu

‡Assistant Professor, Department of Political Science and Social Data Analytics, Penn State University. Email: kevinmunger@gmail.com

1 Introduction

Mark Zuckerberg had plenty to worry about before his blockbuster appearance before the U.S. Senate in April 2018. His company was again the target of intense public backlash after explosive details about Cambridge Analytica's access to user data came to light. More than other controversies before it, this particular scandal brought together all of the public's concerns about internet platforms that had been developing over the previous several years: privacy, manipulation by algorithms, internet companies' scale, subliminal persuasion, and now an added layer of dirty political tricks. Congress had targeted Facebook's CEO with the threat of potential regulation at its disposal and the public's outrage at its back. In the many hours Zuckerberg reportedly spent preparing for his two days of testimony, he likely received coaching on how to explain the logic of advertising auctions and the company's efforts to maintain the "integrity" of its products in the face of disinformation, among other delicate and complex issues not well understood by the public.

Yet for all his diligent preparation, Zuckerberg found himself focusing on the basics. Some of his questioners appeared to confuse rudimentary concepts, such as email and the WhatsApp messaging service. Others invoked conspiracy theories about Facebook secretly listening to its users. In one of his most-discussed answers, Zuckerberg was compelled to explain Facebook's business model to Sen. Orrin Hatch: "Senator, we run ads."[1] Two notable features of these exchanges quickly gained traction on Twitter (a platform with very different features than Facebook, Zuckerberg reassured Sen. Lindsey Graham): They reflected low fluency with basic technological concepts central to politics. And, much of the confusion was emanating from the chairs and ranking members of the Senate committees, whose median age was reportedly nearly 80.[2] It would be difficult to conjure a more vivid demonstration of generational gaps in technological savvy and their impact on public policy.

Ironically, research by Facebook itself had already begun turning up findings suggesting that

[1] See: https://www.theverge.com/2018/4/11/17224184/facebook-mark-zuckerberg-congress-senators and https://www.cnet.com/news/some-senators-in-congress-capitol-hill-just-dont-get-facebook-and-mark-zuckerberg/

[2] See: https://twitter.com/iankoski/status/983780337829449728

age-based differences in online engagement were relevant for political outcomes. A prominent digital voting experiment, conducted in concert with the platform in 2010, uncovered striking evidence of heterogeneity in the effect of sharing "I Voted" stickers to one's friends (Bond et al. 2012, 2017): "The [Facebook GOTV experiment] effect size for those 50 years of age and older versus that of those ages 18 to 24 is nearly 4 times as large for self-reported voting and nearly 8 times as large for information seeking." Turning to a very different form of networked online political activity, the 2016 U.S. presidential election triggered intense scholarly interest in online misinformation. Using distinct data sets and statistical models, several research teams separately reached two main conclusions. First, the overall consumption of low-quality, untrustworthy, or "fake" news was small. Second, the consumption and sharing of this fake news was very unequally distributed — and much higher among older internet users (Guess, Nagler, and Tucker 2019; Barberá 2018; Grinberg et al. 2019; Osmundsen et al. 2020).

The magnitude and consistency of age-based heterogeneities in online political behavior implies some qualitative differences in how people experience digital media. This is suggested by descriptive evidence on both older and younger adults' internet habits. For instance, a review of older adults' internet use patterns finds differences in overall internet skill as well as the kinds of activities they partake in when online when compared to other age groups (Hunsaker and Hargittai 2018). Much more research has focused on younger adults, however. For example, panel surveys have shown significant age-based differences in social media use for political news, with significantly stronger associations with political participation among younger citizens (Holt et al. 2013). Of course, age itself is not likely the driver of these differences. Rather, we posit that age serves as a proxy for some other characteristic that covaries with generational cohort and that plausibly relates to people's experiences with digital media. Literature in sociology and communication has documented the advantages of being a "digital native" as well as the pathologies of the "second digital divide" (Hargittai 2001, 2010).

Motivated by these concerns, we explore the construct of *digital literacy* and argue for its importance to political science. First, we sift through a diffuse multi-disciplinary literature and propose a conceptualization of digital literacy as *online information discernment combined with* *the basic digital skills necessary to attain it.*Given the concept's multifaceted nature, we focus primarily on this "skills" dimension, which captures the kind of basic technological fluency commonly associated with effective use of online tools for political purposes. We then make two key methodological contributions for scholars interested in incorporating the concept into their research. First, adapting and expanding on scholarship in other disciplines, we assess prominent survey batteries proposed to measure skills. Second, we draw attention to a subtle but consequential form of selection bias that has implications for researchers' sampling decisions. We illustrate the importance of these factors in explaining a behavior likely to be related to digital skills: online information retrieval.

In addition to measurement considerations, we also show that the choice of subject pool for surveys is critically important for questions related to digital literacy: We demonstrate that fielding studies on Mechanical Turk (MTurk) is likely to drastically undersample low-skill respondents, which could skew inferences in unexpected ways. Returning to one of the motivations for our investigation, we document with a large national sample that skills do indeed covary with age, with older Americans having lower levels on average. This hints at the possibility that unmeasured variation in digital literacy has driven prior findings on the apparent relationship between age and online behaviors such as sharing low-quality (or "fake") content on social media. Finally, we illustrate these issues with an analysis of online information retrieval accuracy. We conclude with a discussion of how the concept of digital literacy can usefully contribute to several other literatures likely impacted by recent shifts in the online information environment.

2 Skill and Media Modality: A Brief History

The rapid adoption of the internet and social media in the United States has changed the media landscape. But by most ways of counting, the spread of first radio and then television through society happened more rapidly, and each had a larger impact on the daily media diets of the average consumer (Prior 2007). This was only possible because radio and television are *easy* to consume: everyone is trained to listen to human speech from birth, or to listen to speech paired with a visual stimulus. Other than language barriers or the rare niche program, anyone could turn on their radio set or television and share an experience with anyone else listening.

This audience-capacity line of thinking is inspired by Bennett and Iyengar (2008)'s magisterial retrospective on the history of communication scholarship, which argues that the analytic perspectives that scholars find compelling at a given time are driven by their technological and social framework. Importantly, communication theorists of the modernity of the early 20th century were grappling with the novelty of mass society made possible by these broadcast technologies. Analyzing novel, pressing developments is a great angle for scholarship, but this first wave may have been *too* influential — the modernist paradigm continued to dominate theoretical inquiry long after the premises that motivated it failed to obtain.

The internet is different in every respect. It took many years to develop and has been constantly mutating. During its formative years, the only consumers tended to also be producers. Only people with specialized skills could even access online media, which was at first only written text. This early online media was thus produced and consumed by a small number of professionals in academia and tech companies, gradually expanding to geeky hobbyists with enough free time and disposable income to purchase and use the necessary, complicated hardware (Abbate 2000; Burke et al. 2005).

For the past 50 years, television has been the dominant modality for political media. The total supply of television content is constrained by the cost of production and distribution. And televisual content requires minimal skill to appreciate. So, with a small number of notable exceptions,[3] the dominant theories of media effects were focused on *homogeneity*.

The internet inverts this. Central tendencies are simply not that informative. Individuals' experiences are so distinct that heterogeneity should arguably be the baseline expectation.

The technological affordances of online media allow for a much greater variety of content,

[3] In addition to the widespread theory that media effects are heterogeneous in partisanship, Prior (2007) and Arceneaux and Johnson (2013) establish the importance of audience preferences for entertainment limiting the total reach of political media. Mutz (2015) makes a similar case for studying the heterogeneity in audiences' conflict avoidance in understanding the reach of uncivil cable talkshows.

expanding the scope of "politics" beyond the evening news or cable talk show. Furthermore, this variety has increased over time, as more different types of people and organizations produce that content. But this is only one source of increased heterogeneity of media effects due to the expanded diversity of the audience for online media. Unlike a radio or television broadcast, where the range of the experiences among adults exposed to a given piece of content is limited, the range of the experiences among adults exposed to online media is *extremely wide*, at least for the internet audience of the late 2010s.

These *experiences* are created at the intersection of a media consumer and a piece of online media. The classic model of political sophistication in Luskin (1990) conceives of the acquisition of political information as a process with three inputs: access to that information, the motivation to acquire it, and the ability to process it. Access has clearly increased with the web, and Sood and Lelkes (2018) claim that rising education levels suggest increased ability, at least in the aggregate. The key complication, we argue, is that the *difficulty* of acquiring (true) political information on social media is much higher than in other modalities — and that *ability* is currently highly heterogeneous.

Our aim is in part to translate a large literature on this internet *ability* from other disciplines into the realm of political science. This literature begins with Hargittai (2001), who describes the "Second-Level Digital Divide." To that point, concern about the "Digital Divide" was over differential access to the internet. Hargittai's method was participant observation: she sat behind people and watched them use the internet to search for information.

This simple act was revelatory (and is a tool that could still be fruitfully used by researchers to study novel internet technologies). People used the internet *very differently*. They varied considerably in their capacity to find factual information, and in their speed in doing so. Hargittai conceptualized this as "online skills" — a concept that refers explicitly to the actual, validated ability to "to efficiently and effectively find information on the Web." There are of course a variety of different specific skills that comprise one's overall internet ability, and other skills involving related technologies (e.g., "computer skills," related to hardware).

One drawback of this measure of "internet skills" is that directly observing these skills at scale is difficult. Instead, Hargittai (2005) develops and validates a survey measure that serves as a proxy for internet skills. This exercise demonstrated that a battery of survey questions that ask respondents to rate their familiarity with a series of internet terms was most predictive of the underlying internet skills of interest.

3 Digital Literacy: Theoretical Building Blocks

The term *digital literacy* (or *digital media literacy*) is frequently invoked but rarely defined consistently.[4] Possibly for that reason, its boundary is porous: discussions of digital literacy tend to overlap with related concepts such as internet skill (Hargittai 2005), media literacy (Vraga and Tully 2015; Vraga et al. 2015), and digital inequality. Unsurprisingly, then, research on the topic is dispersed across multiple disciplines ranging from sociology and communication (e.g., Koltay 2011) to library and information sciences (e.g., Eshet 2004). Building on existing work, a contribution of this paper is to theoretically situate the concept of digital literacy and specify it in a way that translates to straightforward, valid measures suitable for use in political science.

We begin by postulating that being digitally literate means being able to reliably assess the credibility of information encountered online (e.g., Flanagin and Metzger 2007). This in turn depends on the ability to verify claims and look up answers to questions using a variety of strategies.[5] While this may seem similar to traditional notions of information fluency (Sharkey 2013), it is situated within people's digital environments and the social context they experience online. In other words, we do not conceive of digital literacy as something specifically related to formal information sources (news organizations) or topics of continued interest to scholars (politics, health). A key feature of multifaceted environments is the constant need to assess the credibility of claims and requests, both formal *and* informal — not only while perusing social

[4] "The indistinct use of the term causes ambiguity, and leads to misunderstandings, misconceptions, and poor communication among researchers" (Eshet 2004); Bawden (2008) describes it more bluntly as "a topic whose terminology is very confused" (17).

[5] Such strategies for critically evaluating online information include "lateral reading" (Wineburg and McGrew 2018) and the "SIFT" technique (`https://hapgood.us/2019/06/19/sift-the-four-moves/`).

feeds and news headlines, but also in everyday encounters like phishing attempts and spam in one's email inbox. Whether routine or connected to specific informational needs, all of these tasks require judging what's on the screen in front of them: separating the trustworthy (genuine email communication, professional-quality news, credible claims by friends and acquaintances) from everything else.

Becoming proficient at these judgments requires experience as well as the fundamental skills needed to enable it. In the realm of routine tasks, recognizing a phishing attempt requires familiarity with the mechanics of email. Checking the credibility of a source might require opening a new browser tab (on a desktop or laptop computer) or switching apps (on a mobile or tablet device) — building blocks so essential that they are often bundled alongside higher-level competencies when taught in libraries and schools.

At its core, then, digital literacy consists of a *skills* component and an *information literacy* component. This is implied in some existing scholarship. In a foundational book on the topic, Gilster (1997) asserts that "digital literacy is about mastering ideas, not keystrokes" (15), suggesting the primacy of a more general kind of information literacy. But in the same book, Gilster defines core competencies of digital literacy which include the ability to search the internet and navigate hypertext. Taking the link between skills and information literacy to its logical conclusion, one could argue that literacy is itself a kind of skill. Hargittai and Micheli (2019) identify 10 dimensions of "internet skills," such as interpersonal communication and managing privacy, which collectively amount to a digital citizenship test for the 21st century. One of Hargittai and Micheli's skills dimensions is "ability to find and evaluate information," which corresponds most directly to notions of information literacy or discernment.

This twin conception of digital literacy — information discernment combined with the basic digital skills necessary to attain it — has two advantages. It unifies disparate strands of scholarship while establishing boundaries that separate it from related ideas such as digital savvy and news literacy. At the same time, it allows for tractable measurement: Instead of attempting to detect information literacy, we focus on the skills component as a useful proxy for the whole.

The question of how to define and measure digital literacy returns us again to political sophistication (Luskin 1990), which similarly bundles several components (i.e., knowledge, interest, and abstract reasoning ability). Reviewing the many existing approaches to measuring the concept, Luskin (1987) proposed a type of "recognition and understanding" measure (Converse 1964) that grades respondents on a series of factual questions about the ideological leanings of the parties. This measure intentionally taps the knowledge element of sophistication ("what") rather than assessing directly people's belief systems ("how") or the extent to which they think about politics at all ("how much"). As Luskin argues, "Empirically ... there should be a strong relationship between the 'how much' and 'how' and some factual aspects of the 'what"' (881) — in other words, while it may be theoretically possible to have a sophisticated political belief system built on basic factual misconceptions, it is difficult to envision in practice. Likewise, someone who lacks the digital acumen to download and send a file may be well versed at searching for reliable information online, but the combination would be unusual.[6]

As political sophistication came to be an important moderator in studies of retrospective voting and preference formation, we argue that digital literacy is a crucial factor in online political behavior whose role has to date been obscured by disciplinary practices designed for an earlier media-technological environment. But how should digital literacy — in particular, the skills component we take as a tractable proxy for the whole — be measured?

4 Information Retrieval During an Online Survey

How best to measure "digital literacy" — information discernment combined with the basic digital skills necessary to attain it? We conduct a "horse race" between a suite of measures to see how they perform at predicting which subjects succeed at an online information vetting and retrieval task. The four measures are self-reported age and three survey scales intended to capture an element of digital literacy. We contend that the conception of digital literacy

[6]An interesting corollary is that the skills component lends itself to direct behavioral observation without the need for self-reported survey responses. However, as we discuss below, translating that to usable measures is a nontrivial challenge.

outlined above is flexible enough to encompass multiple skills and competencies (Hargittai and Micheli 2019), and as such, the optimal survey battery may depend on the nature of the research question. For example, does the question concern people at the extremes of digital literacy? Is temporal validity a concern? Are researchers interested in populations that primarily use mobile devices?

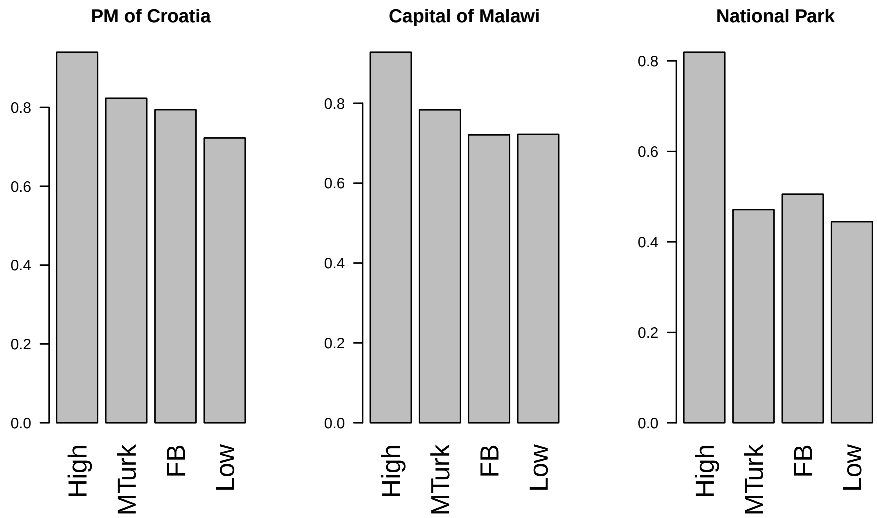
The first that we examine is Hargittai's 21-question "internet skills" battery asking respondents to self-report their familiarity with a series of computer- and internet-related terms, on a 5-point scale (Hargittai 2009). The second is the "power user" scale developed by Sundar and Marathe (2010). This scale consists of 12 questions asking respondents about how they interact with technology, on a 9-point agree-disagree scale. Examples include "I make good use of most of the features available in any technological device" and "Using information technology makes it easier to do my work." We speculate that the lack of proper nouns in this scale could improve "temporal validity" (Munger 2019) over alternatives. To these two, we add a third scale of our own construction: the "low end" scale. This scale adapts the intuition behind the "power user" scale, which was designed to separate high-skill users from everyone else, while ours is designed to separate low-skill users from everyone else. The scales can be found in the Appendix.

We include in our survey instrument a series of three information retrieval tasks of varying degrees of difficulty. These are online information-related tasks of interest to political scientists; to our knowledge, this is the first internet-based survey implementation of these types of tasks. Internet-based surveys can be a drawback for scholars studying political knowledge because they enable the possibility that respondents will "cheat" and look up the answers online (Clifford and Jerit 2016; Smith, Clifford, and Jerit 2020). We use this feature to our advantage, explicitly instructing respondents to look up the answers and intentionally asking questions which are sufficiently obscure to U.S.-based respondents that few could be expected to know the answer.

The three information retrieval questions were:

- Who is the Prime Minister of Croatia? (Andrej Plenković; the presence of the concluding diacritical means they copy+pasted the answer)

Figure 1: Information Retrieval Accuracy Across Four Samples



Percentage of respondents from each sample (Facebook sample, $N = 451$; High DL sample, $N = 83$; Low DL sample, $N = 18$; MTurk sample, $N = 503$) who correctly answer each of three information retrieval questions.

- What is the capital city of Malawi? (Lilongwe)
- What is the only U.S. National Park that begins with the letter "T"? (Theodore Roosevelt National Park)

To ensure that our analysis was not skewed by the particularities of any given sample and to ensure some face validity, we conducted the survey on *four* distinct samples: two large samples drawn from online sources commonly used in political science research, and two small, specialized samples at the likely extremes of digital literacy. One is a sample recruited from MTurk ($N = 503$), a now-ubiquitous source of subjects for many types of social science experiments (Berinsky, Huber, and Lenz 2012). The MTurk interface is somewhat difficult to navigate, and qualitative evidence from Brewer, Morris, and Piper (2016) suggests that this barrier prevents low-skill people from using the platform. As a result, we expect this sample to skew to the high end of digital literacy and to contain a hard floor, below which there will be virtually no respondents.

The second follows Zhang et al. (2018) and Munger et al. (2020) and uses a Facebook ad to recruit survey participants ($N = 451$). Facebook is generally very accessible, and many users have accounts created for them by younger, more tech-savvy relatives to make it easier to keep in touch. Redmiles, Chachra, and Waismeyer (2018) reports that certain groups of Facebook users are much more likely to click on spam, in particular women and lower-skill users. Munger et al. (2020) report that similar groups are more likely to click on these Facebook recruitment ads. As a result, we expect this sample to skew toward the lower end of digital literacy relative to other samples.

Our "high-skill" sample ($N = 83$) was constructed by asking friends and colleagues who work at technology companies to distribute the survey among their workforce. Navigating computer technology is central to these people's careers, and our assumption is thus that they are highly skilled.

In contrast, our "low-skill" sample ($N = 18$) is comprised of people who were taking introductory computer skills classes at the Princeton Public Library and the Brooklyn Public Library. Our assumption here — corroborated by conversations with librarians at these institutions — is that people who were taking the time to learn the basics of computing are lacking in those skills. These respondents may not be the absolute lowest in digital literacy, but this issue begs the question of the composition of the population of "internet users."[7] At a minimum, this sample illustrates that populations of low-digital-literacy respondents do exist, that they have intentions to go online, and that their characteristics differ in important ways from typical samples used by political-science researchers.

The distributions of the correct answers to the three questions across these four initial samples comports with our expectations. On average, the tech-worker "high" sample does the best, and the computer-class "low" sample does the worst, as can be seen in Figure 1.

Focusing on each task separately, it is evident that the first two questions are both similarly straightforward. A single Google search of the exact question will produce one of Google's auto-

[7]Without careening into an epistemic abyss, we consider the way this population is treated by researchers. At any point over the past three decades, the population of internet users is non-representative of the U.S. population; researchers studying online behavior plausibly defend the former population as worthy of study on its own terms. But growth in access to the internet during that time period also means that the population of internet users at time t is not representative of the population of internet users at time $t{+}1$. This is all to say that there is no defensible infimum of computer skills we can use to define the population of internet users today.

populated "answer boxes" with the correct answer. On these questions, our expectations of the relative performance was exactly correct: the MTurk sample did better than the Facebook sample, and they were between the high and low samples.

The third question was selected specifically to require slightly more skill at crafting a search term and navigating the options provided. Here, the only gap is between the "high" sample and everyone else. This suggests that lower-skill individuals, of which there should have been some across the other samples, had difficulty with this question.

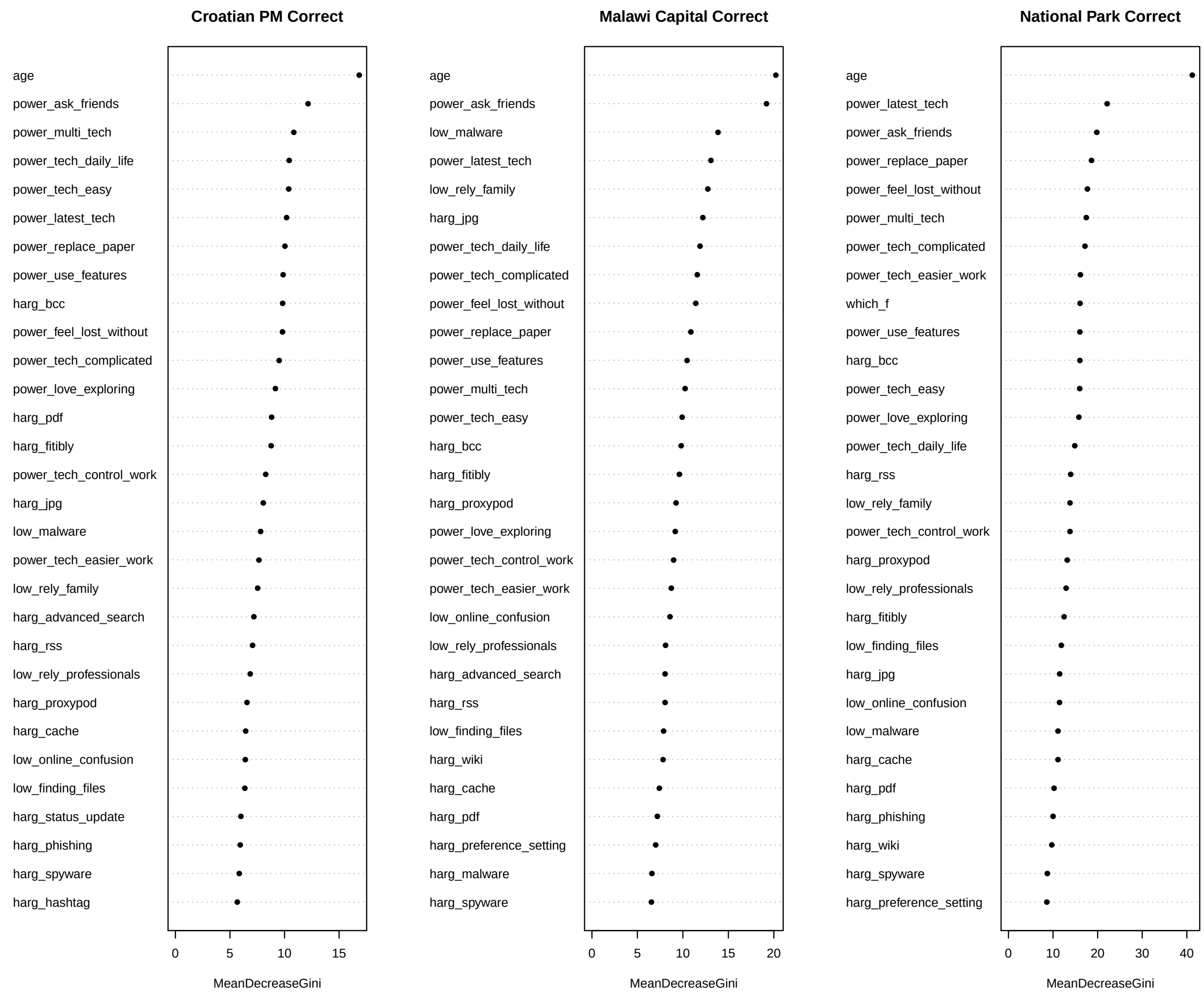
The next step is to conduct a horse race between the existing measures. To do so, we deploy a random-forest model designed to predict whether each respondent correctly answered each of these three information retrieval questions, using the disaggregated survey measures as predictors. Montgomery and Olivella (2018) provide an overview of the utility of these tree-based models for political science data. They are particularly useful for situations in which there are a high number of variables relative to observations, as is the case in our analysis.

Of primary interest in our case is the contribution of each variable to the performance of the classifier. Our use of this model mirrors the logic for its application in Benoit, Munger, and Spirling (2019), where they explain: "Random forests produced estimates of the relative importance of each variable to predicting the outcome, which we can then use to select the most helpful predictors. This approach's main advantages for our problem are accuracy, efficiency, an 'automatic' importance measure, and a low risk of overfitting relative to other tree-based classifiers." We used the default values for the tuning parameters and ran each model with 1,000,000 trees. As a result, the uncertainty from the simulations is reduced to several orders of magnitude smaller than the estimates in all of the analyses reported below.

Figure 2 presents the results of the random forests with the disaggregated scale items, in addition to respondents' age. Age is always the single piece of information that best predicts the respondent's performance, dramatically so in the more difficult National Park question. But the survey questions from the three scales provide plenty of information as well.

Here, the Power User scale is the clear winner. For the Croatian PM and National Park information retrieval tasks, the top seven survey questions in terms of increased predictive accuracy are all drawn from this scale. The Malawi task is more diverse, with two questions from the Low End scale and one from the Internet Skills scale in the top seven.

Figure 2: Increased Classification Accuracy of Information Retrieval



Results of a random-forest classification of 1,046 respondents aggregated across all four samples. Each row represents the decrease in the average purity of leaf nodes when that measure is removed from the analysis. Each column takes the correct response of a different information retrieval question as the binary classification target of the random forest.

We also include an indicator for which sample the respondent was drawn from, "which_f" in the plots.

Reassuringly, adding this variable does relatively little to improve the prediction as to whether the respondent correctly retrieved the information, despite the wide variation in performance between the samples seen in Figure 1. Indeed, for the two easier tasks, the indicator for which sample a respondent belonged to did not enter the top 30 (of 40) predictors displayed in the graph. This suggests that the other measures accurately capture the mechanisms underlying the baseline difference between samples. However, for the harder National Park task, "which_f" shows up in the top ten, suggesting that there is some residual variation to be explained for more complex information retrieval tasks.

5 Distributions of Digital Literacy

Armed with our suite of measures, we now seek to categorize the distribution of digital literacy in three samples of interest to scholars of digital politics. The first two, drawn from Mechanical Turk and Facebook, were described above.

The third is a national sample recruited from Lucid ($N = 2,146$), an online survey platform recently attracting social scientists' attention (Coppock and McClellan 2019). We expect to find individuals in this sample that span the entire range of our scale, although it may still somewhat under-represent people at the lowest end of the digital literacy scale.[8]

Figure 3 plots these distributions, along with either the low or high DL samples discussed above, depending on the measure.

The bottom right panel of Figure 3 analyzes the distribution of the demographic that first motivated this investigation into digital literacy: age. The results are stark. The age distributions for the MTurk and High DL samples are similar to each other and skewed far in the direction of the young, relative to the data from the 2010 U.S. Census (in green, labeled "USA." The true age pyramid should of course be moved to the right to reflect the passage of 9 years). In contrast, the age distribution of the Facebook sample is actually slightly skewed older, with people in their 60s over-represented. The nationally-representative Lucid sample matches the Census numbers closely, suggesting that this sampling was well-conducted.

The top left panel of Figure 3 displays the results for the Internet Skills measure. The full 21-question scale was used for most of the samples, while the shortened 7-question scale was

[8]We collected the data in late 2019, before a documented decline in attentiveness began to be evident in Lucid samples (Aronow et al. 2020).

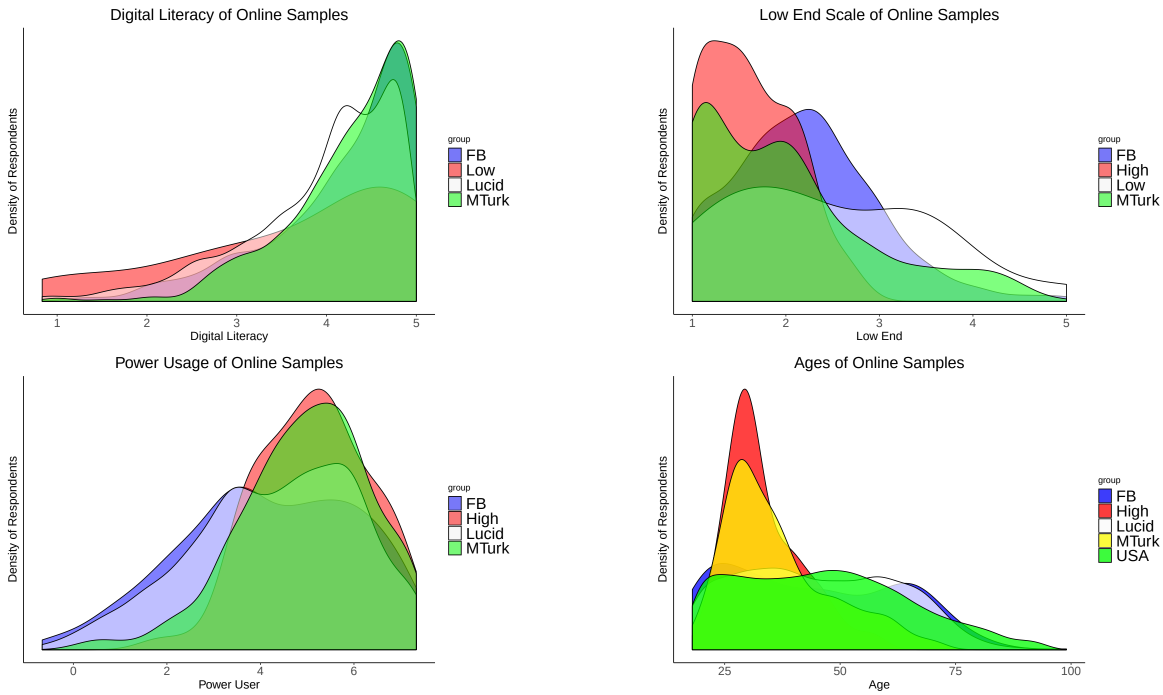


Figure 3: Distributions of Relevant Measures Across the Samples

Each plot represents the distribution of a given variable across 4 different samples (Facebook sample, $N = 451$; High DL sample, $N = 83$; Low DL sample, $N = 18$; MTurk sample, $N = 503$; Lucid sample, $N = 2,146$). The first plot is the distribution of skills of respondents, as measured by the 21 Hargittai identification questions (shortened 7-question scale used for Lucid); the High DL sample is excluded because it is so far skewed to the right that the graph is unreadable. The second plot is the distribution of the "Low End" measure according to our novel 5-question scale, which we did not ask the Lucid respondents. The third plot is the distribution of the "Power User" measure according to the 12-question Power User scale; the Low DL sample is excluded because this measure is not designed to distinguish between people on the lower end. The final plot is the distribution of ages of respondents; the Low DL sample is excluded because very few respondents answered the open-ended prompt with a number; "USA" refers to the population distribution from the 2010 Census.

used for Lucid. As expected, the Low DL sample has a much flatter distribution, with some respondents who report not being familiar with nearly any of the internet terms. The MTurk sample is the least diverse in terms of digital literacy, with close to a hard floor at 2.5 on the 5-point scale. Only 1.4% of MTurk respondents were below this figure, compared to 16.7% of the Low DL sample, 5.1% of Facebook respondents, 5.8% of Lucid respondents, and 0 out of 83 respondents from the High DL sample.[9]

The top right panel shows our novel Low End scale, designed to detect more variation among people lower in digital literacy. The modal High DL and MTurk respondents are at the bottom edge of this scale, although the support for the MTurk distribution does span the entire range. Facebook respondents are more normally distributed, while (as expected) the Low DL sample provides the highest proportion of respondents who score high on the Low End scale.

Finally, the bottom left displays the results of the 12-question Power User scale. This is in many ways the most troubling result for Mechanical Turk: the distribution of this measure for our High DL sample of tech company employees is nearly identical to the distribution for MTurkers. In contrast, the measure is much more broadly distributed across the Facebook and Lucid samples, with a bump on the higher end for the latter.

5.1 Within-Sample Correlations

Figure 3 suggests a potentially serious methodological problem. The nationally representative studies of misinformation on social media during the 2016 election (Guess, Nagler, and Tucker 2019; Grinberg et al. 2019) demonstrated a correlation between age and sharing "fake news." We have suggested that this finding is due to the fact that the age effect is largely — but not entirely — capturing the effect of digital literacy. We demonstrate this relationship in Figure 4, which provides some logic for why the Power User scale performed so well, as well as evidence for the crucial weakness of using MTurk samples for studying online behaviors potentially moderated by digital literacy.

[9] The point of insufficient variation at the low end of digital literacy among MTurk workers was recently noted as well by Hargittai and Shaw (2020).

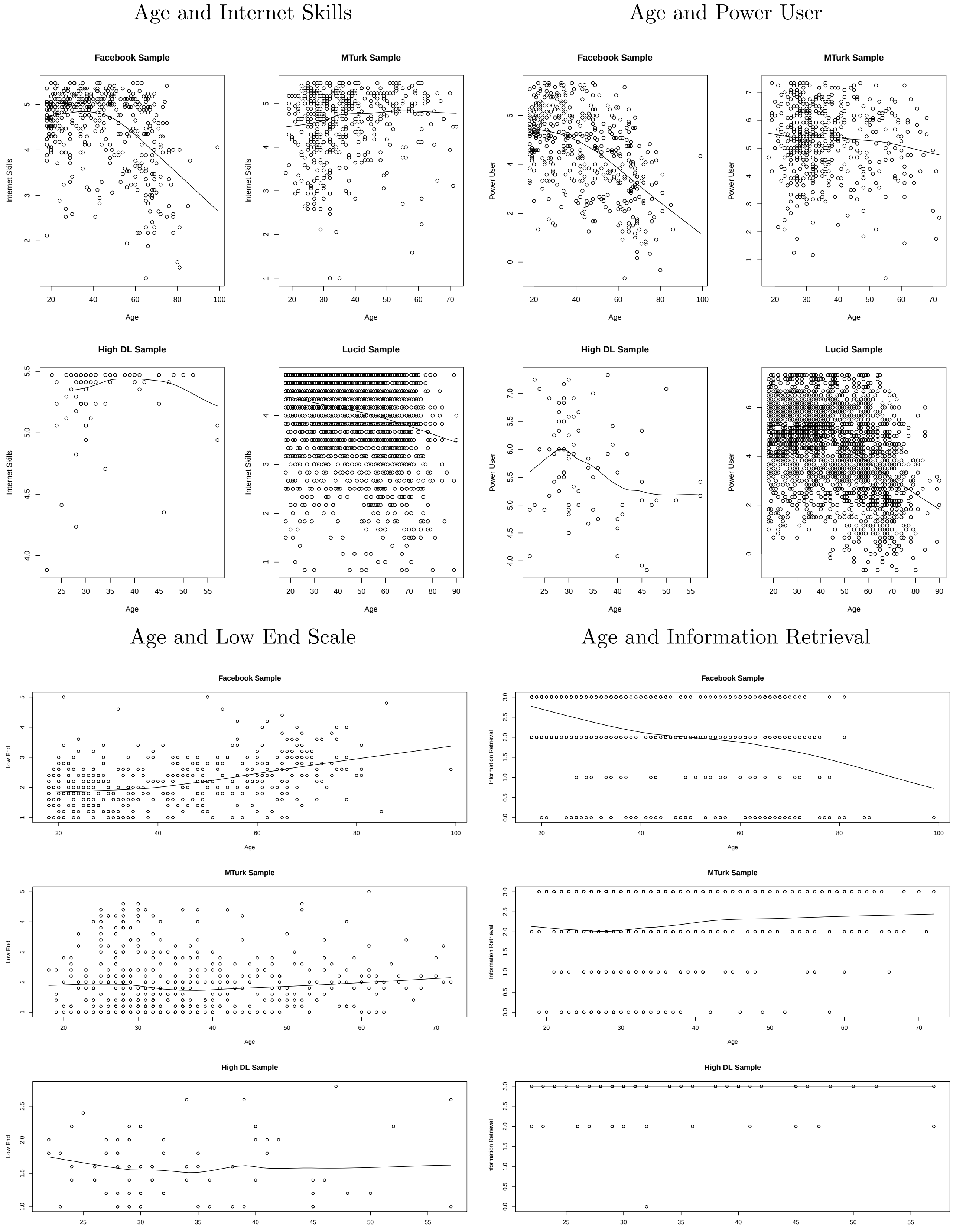


Figure 4: Each scatterplot and loess represents the relationship between age and either Internet Skills (top left), Power User (top right); Low End (bottom left); or information retrieval (from 0 to 3, the number of successful internet searches for information, bottom right) in a given sample (Facebook sample, $N = 443$; High DL sample, $N = 83$; MTurk sample, $N = 503$; Lucid sample, $N = 2,146$). The Low DL sample is not present because too few respondents offered a numerical age.

The top left panel of the first subfigure is evidence of the inverse relationship between age and Internet Skills in the Facebook sample. The loess line of best fit demonstrates the non-linearity of this relationship; the line is flat (even sloping slightly upward at the low end) throughout the 18-50 age range, when it becomes significantly negative.

A similar relationship is found in the Lucid sample, portrayed in the bottom right corner of the first subfigure. In this sample, there is a negative, linear relationship between age and Internet Skills throughout the sample. This represents the best evidence to date of a negative relationship between age and Internet Skills in the United States today. The sample ($N = 2,146$) matches national distributions in age, gender, ethnicity, and region demographics.

However, the top right plot of the first subfigure, using the MTurk sample, demonstrates *no correlation* between age and Internet Skills. The average Internet Skills of the 20-year-olds and 70-year-olds recruited via this platform is the same. A similar non-relationship is observed in the High DL sample in the bottom left plot, where (in accordance with our purposive sampling) a majority of respondents scored the maximum of the scale.[10]

The trends are similar in the second subfigure, Age and Power User. Again, there is a negative relationship between age and Power User in the Facebook and Lucid samples, and while the relationship is negative rather than flat in the MTurk sample, the relationship is quite weak. The big difference is in the High DL sample, in the bottom left panel. Unlike for Internet Skills, there is no ceiling effect for Power User, and we see a non-linearity in this sample, peaking at around age 30. This has some face validity, but we note that the sample size is not large enough to allow for high confidence in this trend.

The third subfigure plots the relationship between Age and Low End. The trends are the same as for Internet Skill, but inverted: there is a positive relationship between age and Low End on Facebook, but no such relationship in the High DL or MTurk samples.

Although we have demonstrated the validity of these scales for predicting respondents' capacity for information retrieval, the fourth subfigure of Figure 4 presents as a robustness

[10]We cannot perform the same analysis on the Low DL scale because too few respondents provided us with their age. Only 7 provided a numeric response in the open-ended text field; several of the other respondents provided responses such as (paraphrased for respondent privacy) "Too old for nosy questions" and "Old enough."

check the bivariate relationship between age and information retrieval in the various samples. There is a strongly negative relationship between age and information retrieval in the Facebook sample, although this time the slope is close to constant and negative across the age range. By contrast, there is no evidence of a negative relationship between age and information retrieval in the MTurk sample — in fact, there is a weak but *positive* relationship among people 30 and older.

Presenting this another way, Table 1 displays a series of regressions with our index of three information retrieval questions as the dependent variable. In each panel, using the Facebook sample, the first two columns show the predicted negative relationship between age and information retrieval, even with the inclusion of the Internet Skills measure in panel (a), Power User scale in panel (b), and Low End scale in panel (c). However, the next two columns replicate the analysis on the MTurk sample and find strong evidence of the *exact opposite* relationship: age is here positively correlated with information retrieval, with nearly identical magnitude and standard errors. In both samples, the various survey measures are highly positively correlated with information retrieval.

This result can be described as an example of conditioning on a collider, a form of sample selection bias (Pearl 2009). The issue parallels the canonical examples of a non-relationship between SAT scores and GPA in selective colleges, or the non-relationship between height and performance among NBA players. In each case, individuals who score high on the former measure are more likely to be included in the sample; individuals who are included in the sample despite scoring low on the former measure are likely to possess other traits that contribute to their performance within the sample.

We would like to be able to estimate the effect of age and digital literacy on information retrieval. However, to do that we need to sample from the general population. In the present case, age and digital literacy are causally related to being an MTurk worker. Lower-digital-literacy internet users are less likely to be aware of the platform, and less likely to be able to navigate its non-intuitive interface.[11] Figure 5 visualizes the problem using Pearl's graph-

[11] Brewer, Morris, and Piper (2016) perform a qualitative analysis on a small sample of older adults who have

Table 1: Information Retrieval and Age/Digital Literacy Across Samples

(a) Internet Skills

	Facebook Sample		MTurk Sample	
Internet Skills		0.349^{***}		0.362^{***}
		(0.062)		(0.055)
Age	-0.019^{***}	-0.013^{***}	0.014^{***}	0.011^{***}
	(0.003)	(0.003)	(0.004)	(0.004)
Constant	2.881^{***}	1.038^{***}	1.581^{***}	0.036
	(0.131)	(0.354)	(0.145)	(0.272)
Observations	442	442	503	503
R^2	0.100	0.160	0.025	0.103

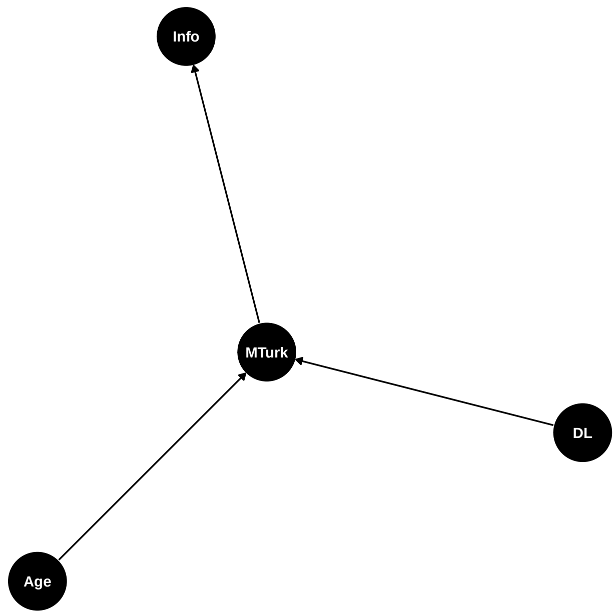
(b) Power User

	Facebook Sample		MTurk Sample	
Power User		0.081^{**}		0.124^{***}
		(0.035)		(0.035)
Age	-0.019^{***}	-0.015^{***}	0.014^{***}	0.015^{***}
	(0.003)	(0.003)	(0.004)	(0.004)
Constant	2.881^{***}	2.349^{***}	1.581^{***}	0.883^{***}
	(0.131)	(0.265)	(0.145)	(0.246)
Observations	442	442	503	503
R^2	0.100	0.111	0.025	0.048

(c) Low End Scale

	Facebook Sample		MTurk Sample	
Low End		-0.177^{**}		-0.263^{***}
		(0.072)		(0.046)
Age	-0.019^{***}	-0.016^{***}	0.014^{***}	0.013^{***}
	(0.003)	(0.003)	(0.004)	(0.004)
Constant	2.881^{***}	3.141^{***}	1.581^{***}	2.115^{***}
	(0.131)	(0.168)	(0.145)	(0.169)
Observations	442	442	503	503
R^2	0.100	0.112	0.025	0.084

Figure 5: Directed Acyclic Graph of Selection Process



ical framework. This selection process means that the within the MTurk sample, the causal relationship between age and information retrieval is broken.

As a result, experimental studies of digital media effects or online misinformation conducted on samples recruited from MTurk are unlikely to accurately estimate the role of age as a treatment effect moderator. Furthermore, as the first panel of Figure 3 demonstrates, there are close to zero MTurkers who are below a threshold of Internet Skills or Power User. Given the highly unequal distribution of engagement and sharing of Fake News during the 2016 election, concentrated among the elderly, it is likely that the most important respondents (who would be influential observations in any statistical analysis) are precisely those who are structurally excluded from MTurk.

not used Mturk, signing them up for the platform and interviewing them about the experience. Although these subjects generally reported being comfortable using computers, they could not complete basic tasks on Mturk.

6 Literacies and Heterogeneity in Political Science

In this paper we argue that taking digital media seriously requires moving away from the assumption of media effect homogeneity developed in the broadcast era. Specifically, important heterogeneity in digital media effects can be captured through the digital literacy construct. We conceptualize digital literacy as having two intertwined components — information literacy and computer/web skill — and provide a validated survey measure based on using skill as a proxy for the whole.

We demonstrate that digital literacy varies considerably among populations frequently used by political scientists. In particular, we show that samples from MTurk contain vanishingly few low-digital-literacy respondents — precisely the population among whom we might expect to find the largest persuasive effects of digital media messages (including misinformation). We recommend that MTurk not be used for studies of digital media effects in the absence of strong theoretical reasons to expect effect homogeneity.

Other disciplines are grappling with the implications of substantively meaningful new forms of heterogeneity for common research practices. In psychology, the Cognitive Reflection Test (CRT) (Frederick 2005) was developed to measure "analytic cognitive style," a disposition that has been shown to covary with psychological and political attributes (e.g., less reflection is associated with paranormal belief and religious belief; see Pennycook et al. 2016). More recently, analytic cognitive styles have been shown to predict lower perceived accuracy of fake news headlines on social media (Pennycook and Rand 2019). Although CRT scores appear to be fairly stable over time, there is evidence that the standard practice of relying on more experienced workers on MTurk could "conceivably inflate CRT scores observed in online samples and undermine the predictive accuracy of the CRT" (Chandler, Mueller, and Paolacci 2014, Study 2). This example similarly illustrates how endogenous selection bias can affect inferences: In this case, attentiveness or other forms of "non-naïveté" predict both inclusion in "high-quality" MTurk samples and high CRT, which is itself an important psychological moderator.

A broader question is how political science should handle novel online platforms for subject recruitment. The case of MTurk is illustrative. Berinsky, Huber, and Lenz (2012) "introduced" the platform to the discipline, and while their validation work is careful and nuanced, it has frequently been cited to imply that MTurk is generally "okay to use."[12] The article made a large impact and is overwhelmingly the most cited article published in *Political Analysis* in the past decade. Numerous papers have argued about the merits of MTurk as a respondent pool for experimental studies. Coppock (2019), the most recent and comprehensive, establishes that a wide variety of experimental findings generated from nationally representative surveys can be replicated using MTurk samples. The reasoning is that since treatment effects are similar for many different types of subjects, the composition of online convenience samples along commonly measured demographic and political characteristics is relatively unimportant for recovering experimental treatment effects. Crucially, however, results about the generalizability of MTurk samples are not themselves generalizable to all possible experiments.

They are also not necessarily generalizable to alternative online convenience sample marketplaces. For example, Coppock and McClellan (2019) explore and offer justification for the use of Lucid, a source of research subjects used in this paper. Aside from the validation exercise, the paper offers a useful discussion of the scientific value of convenience samples for testing theories. Coppock and McClellan accurately observe that concerns about external validity are often poorly motivated. Whether experiments conducted on a convenience sample and a nationally representative sample produce identical treatment effects is immaterial; what matters is whether a given sample is theoretically relevant. They propose, for example, that a sample of French speakers would serve as an inappropriate sample to test a theory about the effect of reading an English-language newspaper. *Literacy* is self-evidently a crucial moderator of textual media effects.

However, we would qualify the claim that "Whether or not future experiments will also exhibit low treatment effect heterogeneity is, of course, only a matter of speculation." We

[12] The sociological processes by which political methodology deems certain elements of research design generally acceptable are central to the practice of political science but have largely escaped systematic study within the discipline. For example, it is possible to think of MTurk as a "trading zone" facilitating exchanges at the intersection of multiple fields and intellectual approaches (Collins, Evans, and Gorman 2007).

argue that digital literacy is likely to be a key moderator of digital media treatment effects, that it varies widely in the current U.S. population (and that it does so even among the current population of internet users), and that this is a significant problem for opt-in crowdworker platforms like MTurk for which digital literacy affects selection into the sample.

The trend of political life increasingly taking place online is not, we argue, "only a matter of speculation." Media technology has radically increased media heterogeneity, a development that shows no signs of abating. This is perhaps a problem for the ecological validity of a given media survey experiment, as a greater variety of stimuli are thus necessary to ensure a representative sample of even a specific type of media (Hovland, Lumsdaine, and Sheffield 1949). More immediately relevant is the continuing existence of the "second digital divide" in computer skills identified by Hargittai 20 years ago. In the absence of an unprecedented increase in the level of digital literacy among those at the bottom of the distribution, we have strong reason to expect that future experiments will exhibit greater effect heterogeneity along this dimension. But only, of course, if those experiments are conducted using samples with sufficient variation in the moderator, and valid measures of it.

7 Conclusion

As awareness increases of the potential for endogenous selection of digital literacy in commonly used samples, scholars will need to grapple with its substantive importance as a moderator in literatures not directly related to the study of online misinformation. Below we discuss three additional areas for exploration of effect heterogeneity by digital literacy. In addition to sampling considerations, these areas also raise questions about the specific measures to be used, which will reflect overlapping but distinct dimensions of the multifaceted construct of digital literacy.

Political knowledge While political knowledge has long been established as a strong predictor of issue-position stability and ideological constraint, Kleinberg and Lau (2019) find that this relationship is now *reversed* for people belonging to the "internet generation." People for whom searching for information online is second nature do not need as much political information stored in their biological memories because they are able to access that information in their digital memories. These findings are consistent with psychological research that conceptualizes people's use of the internet as a kind of external or "transactive" memory (Sparrow, Liu, and Wegner 2011). Accordingly, people are better at remembering *where* to find information than the information itself if they expect to be able to find it later — even if this makes them think that they are more knowledgeable than they actually are (Fisher, Goddu, and Keil 2015).

Future research on the determinants and consequences of political knowledge will need to explicitly take into account variation in individuals' ability to seek out and process online information. Not only might the effect of knowledge vary across levels of digital literacy, but knowledge itself might function differently for people aware that answers will always be at their fingertips. Smith, Clifford, and Jerit (2020) suggest that "Scholars who are interested in measuring political knowledge should take efforts to minimize and diagnose search behavior," but this assumes a static, crystallized view of knowledge that may no longer hold for people who effectively externalize their store of factual information.

Nudges and defaults Behavioral scientists have demonstrated that classes of relatively low-cost interventions can have outsized effects. These "nudges" have been promoted as a way to guide human decisions in a prosocial direction while preserving liberty of choice, as in the case of default options (Thaler and Sunstein 2009). Scholarship on the topic has focused on domains with a clear public welfare dimension, such as education and public health. But the insights of behavioral economics can be fruitfully applied to internet media, as contemporary accounts overlook the hidden obstacles and defaults that structure people's behavior (Lorenz-Spreen et al. 2020). To take a simple example, modern web browsers come pre-loaded with bookmarks for large news and entertainment sites. Many people still use portals for email and other services which link to headlines, weather and other information. Sometimes, such sites automatically load on startup or with a new tab. It is not hard to customize one's settings, but the perceived cost of doing so may be too high for people lacking in digital literacy, with observable implications for political news diets (e.g., Guess 2021).

The effects of online choice architecture are not always innocuous, as more recent writing on "sludge" (Thaler 2018) and "dark patterns" (Mathur et al. 2019) has documented. As worries about online privacy and surveillance become more acute, the ability to protect oneself from insidious efforts to influence consumer and political choices will depend on what Hargittai and Micheli (2019) call "awareness of what is possible" — a dimension of internet skills comprising knowledge about default settings that can be changed. This arguably also covers defensive measures that can be taken against malicious or unscrupulous actors, such as installing blockers for illicit tracking. At a more basic level, people lacking in digital literacy may be unable to defend themselves against clickbait, misleading advertisements, and spam (perhaps political in nature; Perlstein 2012).

Microtargeting and campaign persuasion The possibility that digital literacy captures heretofore unobserved heterogeneity in people's responses to online "sludge" raises more general questions about the effects of modern campaign techniques. Evidence already suggests that online advertisements generate substantial heterogeneity; Kaptein and Eckles (2012) find that heterogeneity in social influence strategies is large relative to the average effect, for example. Moreover, since ads follow the same rules of "engagement" as other types of online content, campaign targeting of favored demographic and political subgroups is subject to feedback loops in which users most likely to respond to appeals will become even more likely to be targeted in the future via platforms' ad optimization algorithms (e.g., Eckles, Gordon, and Johnson 2018). Given generally low clickthrough rates, the kinds of people who are most likely to engage with commercial or political appeals on social media has important implications for democratic participation, representation, and campaign strategy. Future research should explore whether digital literacy explains variation in this important but understudied online political behavior.

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Appendix

Survey Questions

"Digital Literacy" Scale (adapted from Hargittai 2009)

How familiar are you with the following computer and Internet-related items? Please choose a number between 1 and 5 where 1 represents "no understanding" and 5 represents "full understanding" of the item.

- Phishing
- Preference Setting
- App
- Hashtag
- Social Media
- Status Update
- Spyware
- Selfie
- Wiki
- Advanced Search
- PDF

Next screen:

- Tagging
- Tablet
- Smartphone
- JPG
- Malware
- Cache
- BCC (on email)
- RSS
- Proxypod
- Fitibly

(last two items are intentionally made up)

Power User Scale (adapted from Sundar and Marathe 2010)

Please indicate your agreement with the following statements on a scale of -4 = Strongly Disagree to 4 = Strongly Agree.

- I think most technological gadgets are complicated to use.
- I make good use of most of the features available in any technological device.
- I have to have the latest available upgrades of the technological devices that I use.
- Use of information technology has almost replaced my use of paper.
- I love exploring all the features that any technological gadget has to offer.
- I often find myself using many technological devices simultaneously.

Next screen:

- I prefer to ask friends how to use any new technological gadget instead of trying to figure it out myself.
- Using any technological device comes easy to me.
- I feel like information technology is a part of my daily life.
- Using information technology gives me greater control over my work environment.
- Using information technology makes it easier to do my work.
- I would feel lost without information technology.

Low End Scale

Please indicate how often these statements apply to you. [Never / Almost never / Occasionally / Somewhat often / Very often]

- I rely on family members to introduce me to new technology.
- I have professionals (such as the Geek Squad) or family members take a look at my
- computer when something isn't working.
- A lot of the things I see online confuse me.
- I have problems with viruses and malware on my computer.
- I have trouble finding things that I've saved on my computer.