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Stocks, Flows, and Risk Response to Pandemic Data

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During the coronavirus disease 2019 (COVID-19) pandemic, data regarding new infections were commonly presented and used to guide policy decisions (e.g., whether to close schools) and personal choices (e.g., whether to dine at a restaurant). In this manuscript, we highlight a critical aspect of pandemic data that can pose a challenge for people trying to reason about it. Data on infections—like much time series data—can be presented as either stocks (the total number of cases) or flows (the number of new cases over some interval). We show that seeing the same data presented in one format versus the other can shift judgments of risk and behavioral intentions. Specifically, when participants were shown data that depicted the number of new cases each day (flow) decreasing, they judged the current risk of COVID-19 to be lower than participants who were shown the same data as the total (cumulative) number of cases (stock), which—by its nature—continued to increase. Risk appraisal, in turn, predicted a wide array of behavioral intentions (e.g., likelihood of dining indoors at a restaurant). Thus, the choice of how to present pandemic data can lead people to different conclusions about risk and can have practical consequences for risky behavior.

Public Significance Statement
Seemingly minor visualization choices regarding how to present pandemic data can affect the public's judgments of risk and corresponding behavioral intentions. When the number of new coronavirus disease 2019 (COVID-19) cases is in a period of day-to-day decline, people judge the risk of COVID-19 to be greater when shown the data as cumulative totals (over time) compared to when the same data are presented as number of new cases (over time).

Keywords: risk perceptions, data visualization, public health, judgment and decision making

In late 2019, the first known cases of coronavirus disease 2019 (COVID-19) began to emerge in humans. By April 2020, over a million confirmed cases of COVID-19 had been documented (Johns Hopkins CSSE, 2020). By November 2020, that number had climbed to over 50 million. Along the way, governmental agencies, statisticians, and news media outlets tracked the progression of the virus, reporting on its day-to-day march across the globe. People rely on communicated reports from these experts to guide their individual-level response to the pandemic. Apart from the question of whether national and local governments have officially sanctioned the reopening of public life, people ultimately decide for themselves whether to leave the house, book appointments, and gather with others.

Data can guide these personal choices, and these choices can make the difference between life and death for individuals and others they might infect. Thus, it is not surprising that data regarding the spread of COVID-19 came to feel omnipresent. For example, throughout 2020, *The New York Times* tracked and reported every single new confirmed COVID-19 case in the U.S. They featured this information prominently on their webpage and provided an interactive infographic updated daily (Coronavirus Map: Tracking the Global Outbreak; New York Times, 2020).

Data can be presented in different ways, and unscrupulous actors can create visualizations that can be deliberately misleading (Cairo, 2019; Huff, 1954). But even principled actors make choices—including seemingly trivial or minor choices—when presenting data, and these choices can have consequences. If the choices communicators make regarding how to present COVID-19 data affect how others interpret the data, then interpretation could affect how people appraise the current risk of the virus and, in turn, inform their individual-level decisions about behavior. Advice and mandates of epidemiologists and policy makers may fall on deaf ears should people have already made up their data-informed minds as to the risk severity of the crisis.

What different formats can pandemic data take, and how might these formats have systematic, even divergent consequences for risk appraisal and decision making? The present investigation addresses this question by highlighting the fact that one prominent type of pandemic data—specifically, time series data tracking infections as they develop—are commonly presented in two different ways: as cumulative totals (stocks) or as new cases (flows). While other metrics can be, and are, tracked and presented in different ways

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(e.g., active cases and resolved cases), we focus on these two presentation types because of their prevalence in the media (e.g., *The New York Times*) and government (e.g., the Centers for Disease Control and Prevention [CDC] example in Figure 1). We argue and observe in a preregistered experiment that this choice of presentation format impacts people's judgments about risk and their intentions to engage in risky behaviors. These findings call for caution among those tasked with communicating risk when deciding exactly how to format pandemic data in the best interest of the public.

Data Format: Presenting Time Series Data as Stocks or Flows

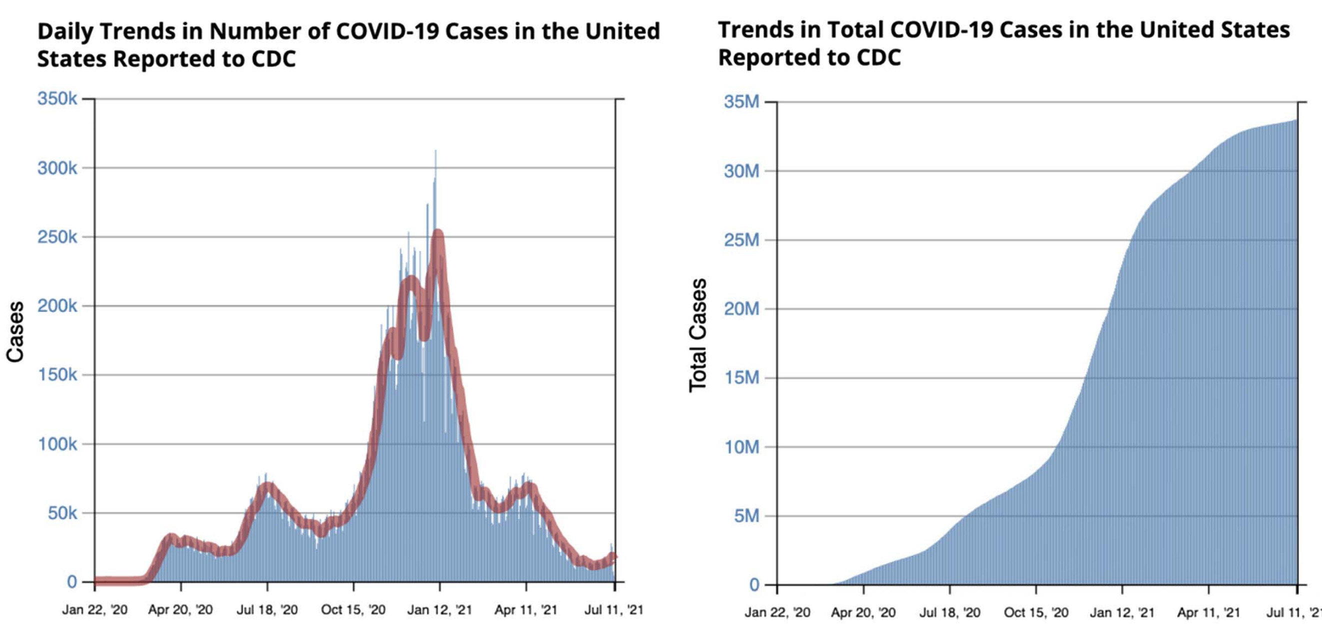
Time series data reflect quantitative information measured over successive periods of time. The temporal nature of such data—including pandemic infection data—means that it can be formatted in different ways. One reasonable way to present time series data is to show the entire quantity—the *stock*—at each point in time. For COVID-19, *stock*-based data presentations report the total (cumulative) number of infections. Another reasonable way to present the same data is to show changes to the quantity—the *flow*—at each point in time. For COVID-19, the analogous *flow*-based presentations would be the number of new infections at each period (e.g., each day). Both presentation formats—*stock-based* and *flow-based*—are used commonly by prominent communicators like the media and government organizations. For example, Figure 1 shows visualizations of U.S. COVID-19 data in both presentation types—new cases per day (flow, left panel) and cumulative cases (stock, right panel) from the Centers for Disease Control and Prevention [CDC] (2020). We note that data from the CDC, as well as the data we use in our study, track cases of COVID-19 confirmed via testing, and thus necessarily underestimate the number of true infections (Rahmandad et al., 2021). Henceforth, our references to "cases" should be interpreted in light of this underestimation.

It might seem reasonable to assume these two formats are interchangeable, as both presentation formats are based on the same data and contain the same underlying information. The logic of calculus allows transformation from one to the other: The cumulative number of cases (stock) is the integral of the number of new cases (flow), and the number of new cases (flow) is the derivative of the cumulative number of cases (stock). While the visualizations in Figure 1 lack the necessary precision for exact conversions between the two, translating the basic features from one to the other is, in theory, a feasible task: Peaks and nadirs in new cases (flow) correspond to inflection points in cumulative cases (stock), and higher levels in new cases (flow) correspond to steeper slopes in cumulative cases (stock). Should viewers wish to see stock data formatted as a flow or flow data formatted as a stock, it is plausible they could simply conjure the other visualization in their mind's eye.

In practice, however, the logic of accumulation inherent to such a conversion task can befuddle even highly educated people (Booth Sweeney & Sterman, 2000; Cronin et al., 2009; Sterman, 2002). In one example, Cronin et al. (2009) gave MIT graduate students a task that required converting from flows to a stock. Participants were shown a simple figure representing the number of people entering and leaving a department store over time (i.e., flow-based presentation of data) and asked "During which minute were the most people in the store?" and "During which minute were the fewest people in the store?" (i.e., stock-based interpretation of data). Fewer than one third of these students—all of whom had taken a course in calculus—got both of these seemingly straight forward questions

Figure 1

New COVID-19 Cases Per Day in the U.S. (Left Panel) and Cummulative Cases (Right) Panel as Displayed by the Centers for Disease Control and Prevention (CDC; CDC.gov) as of July 11, 2021



Note. See the online article for the color version of this figure.

correct. Subsequent work has reinforced the persistence and robustness of these types of mistakes, often referred to as *stock–flow failure* (Brunstein et al., 2010; Gonzalez et al., 2017, 2018; Gonzalez & Wong, 2012; Newell et al., 2016). In this work, the focus is typically on problems with a normatively correct answer (e.g., the level of an inflow required to stabilize the accumulation; Gonzalez et al., 2018), which—even in the face of clever interventions designed to help—the typical participant often gets wrong.

The present investigation builds from these documented failures of people's reasoning in two important ways. First, because of the difficulty inherent to converting between the two, people are unlikely to attempt a spontaneous conversion from one format to the other. Accordingly, and second, people might form different, possibly divergent mental representations of the same data depending on the presentation format in which it is presented. Indeed, research suggests that people—in general—reason about data in the format presented (Cleveland & McGill, 1984; Kahneman, 2011; Lurie & Mason, 2007; Slovic, 1972). For instance, investors in the stock market report different expectations for future performance when considering returns versus prices (Glaser et al., 2007, 2019) and people become more sensitive to changes when they see data presented in a way that makes those changes more salient (Andreassen, 1988; Andreassen & Kraus, 1990). With time series data (COVID-19 data—and other pandemic data more broadly, including vaccination numbers—representing an important and focal case), presenting data as flows (e.g., new cases) versus stocks (e.g., total cases) can make different types of changes more salient. In the left panel of Figure 1, the peaks in new cases (flow) are quite salient, as are the preceding upward and ensuing downward slopes. However, these changes within the data are less salient in the right panel of Figure 1, as this information is captured only by harder to see changes in the concavity of total cases (stock). The total case presentation instead makes the overall upward trend in cases more salient.

Accordingly, the present investigation considers not *stock–flow failures* in attempting to convert or assimilate information between the two formats but, instead, *stock–flow inconsistency* in judgment when comparing responses from people who see data presented either (and only) as a stock or flow. In this sense, while our predictions build from past work on stock–flow failures, our investigation is more closely related to Spiller et al. (2020), which examined more directly the impact of stock- and flow-based presentations on mental representations and judgment. In a series of experiments, they presented participants with the same underlying time series data visualized as either stocks or flows and asked participants to make judgments drawing from the data. Despite containing the same information, judgments predictably diverged based on presentation format. Specifically, judgments diverged when one presentation format featured a salient negative slope while the other featured a salient positive slope. In one example, people were shown U.S. employment data as either a stock (i.e., total number employed) or a flow (i.e., change in employment) across the years 2007–2013. In 2009, the total number of jobs (stock) was decreasing. However, the rate of job loss was slowing: each month saw the loss of fewer jobs than the month before. The year 2009 was also President Obama's first year in office. When shown the stock presentation—which featured a decreasing trend—people expressed a belief that Obama had a negative impact on the economy during his first year in office. When shown the same data as a flow—which featured an increasing trend (from more negative to less negative)—people expressed a belief that Obama had a positive impact on the economy during his first year in office.

This evidence points to the possibility that presenting pandemic data as stocks or flows might lead people to different conclusions about the severity of risk currently associated with COVID-19. Such a possibility seems particularly likely under the circumstances in which the number of new daily cases is decreasing but cumulative cases are still increasing (i.e., the series exhibit opposing trends). Though it represents only one scenario within the broader framework in which stocks and flows can move in the same direction or opposite directions, this specification has risen to wide practical prominence in light of the COVID-19 pandemic in which the flow of cases can repeatedly fall, while the overall stock necessarily continues to rise. For reasons detailed in the next section regarding how the public responds to COVID-19 data (as well as that of other potential pandemics), the present investigation targets exactly this state of affairs.

Subjective Risk and Behavioral Response

In addition, past work suggests that the format data take (e.g., stock vs. flow) can influence how people mentally represent that data and the conclusions they draw from it. We extend this past work by examing the effects of presentation format in the substantively important context of pandemic data. Further, we focus on dependent measures that relate to how people respond to the virus: judgments of current risk and behavioral intentions for potentially risky behaviors (e.g., eating indoors at a restaurant). We propose that presenting pandemic data as the cumulative number of cases (stock) versus the number of new cases (flow) can, in situations where the number of new cases each day is descreasing, lead to different levels of perceived risk. We further propose that these differences in risk perception impact individual-level likelihood of engaging in risky behaviors.

Risk communication is at the heart of data presentation in a pandemic. Considering data presentation format as an element of this communication is consistent with the idea that the manner in which information is shared can color risk perception (Fischhoff et al., 1993). A change in visualization can lead to corresponding changes in how observers reason about risk and uncertainty, even when the varying visualizations summarize the same data. Past research on risk communication speaks to topics as varied as catching a bus to catching a sexually transmitted disease to climate change (Hullman et al., 2018; Kay et al., 2016; Reyna & Adam, 2003; Sterman 2008). This past work consistently underscores the importance of communication in conveying risk-related information to a wide audience of laypeople. Insofar as time series pandemic data represent figures pertaining to negative, risky outcomes (e.g., infections), it stands to reason that stock and flow presentation format might inform how individuals evaluate risk.

Mass communication is but one means by which to transmit risk-related information. Still, regardless of the means by which it arrives at the individual for consideration, that individual mentally converts from objective information to a felt sense of riskiness (Gallistel et al., 2014; Loewenstein et al., 2001). While numerical data undergo a largely successful conversion to subjective risk, certain elements tend to get lost in translation (Weber & Hilton, 1990; Windschitl & Weber, 1999). Accordingly, risk perceptions do not always align with true risk level (Slovic, 1987; Slovic et al., 1982;

Slovic & Peters, 2006) and can differ across individuals and frames (Weber & Milliman, 1997). In that research tradition, a given prospect comes to feel less risky or more risky than one taking a normative perspective might argue it should. Consideration of stocks and flows allows the present investigation to ask a related, though different, conceptual question: whether a given prospect may feel more or less risky as a function of how the same data are presented.

Elsewhere, subjective risk has been brought to bear on downstream, risk-related action (e.g., Epstein, 1994). As an example, Maglio and Polman (2016) described to research participants an objective risk of 15% that a bottle of wine was defective. One group learned that the risk was increasing (up from a previous 10% chance), while another group learned that the risk was decreasing (down from a previous 20%). The latter, falling trend made the risk feel less risky—and made participants more willing to take that risk in trying a bottle. Similar effects of rising and falling forecasts on subjective risk and action have been applied to widespread, global issues (e.g., climate change; Hohle & Teigen, 2015). At a yet broader level, subjective risk perception impacts how people choose and act in facing health and medical decisions (Brewer et al., 2007; Reyna & Brainerd, 2007; Reyna & Lloyd, 2006). The COVID-19 pandemic sits at the intersection of substantial, global concern and health and medical decisions. This allows us to extrapolate from these prior investigations to clear predictions for how data presentation format should impact not only subjective risk but also decisions that result therefrom.

The Current Investigation

We examine whether seeing pandemic data as a stock (time series of cumulative number of cases) versus a flow (time series of new cases) can lead to differences in risk perceptions and behavioral intentions. We note again that this focus diverges from the type of question typically asked by those studying *stock–flow failure* (e.g., Gonzalez et al., 2018) in that there is no normatively correct benchmark against which to evaluate the accuracy of participants' judgments. Our focus, instead, is on *stock–flow inconsistency* in judgments arising between presentation formats. While such inconsistencies might be viewed as failures in a sense, the lack of an objective marker of accuracy makes it hard to say who is wrong. Because of this, we see the goal of our investigation less as identifying a problem in need of a solution (e.g., how to improve the accuracy of conversion between the two) than as identifying the importance of a prominent factor in a pandemic data—choice of stock versus flow presentation format—that can predictably influence judgments.

We hypothesize that differences between these two commonly used presentation formats are most likely to emerge when one format depicts a rising trend while the other depicts a falling trend—in other words, when the trends point in opposite directions, so too will subjective risk and planned action. Beyond strictly stocks and flows, people's appraisals—including evaluations in the present and forecasts for the future—are driven by salient trends (Andreassen, 1988; Andreassen & Kraus, 1990; Freyd & Finke, 1984; McKenzie & Liersch, 2011; Spiller et al., 2020; Thomson & Oppenheimer, 2016; Wagenaar & Sagaria, 1975). As a result, we hypothesize that people's perceptions of risk are disproportionately affected by the salient trend highlighted in stock and flow formatting, which may differ across the two different presentations of the same data. In particular, while the underlying process may hold across trends, we study a case in which the different presentations of the same data take on different signs (as before, one rising, one falling) not only to maximize the ability to detect differences between presentations but also in light of the fact that this scenario is especially prominent in the midst of an ongoing pandemic, meaning that how people respond to it can truncate or prolong the duration of the pandemic.

The cumulative number of pandemic infection cases can only increase. In other words, this particular stock is an absorbing state that can never move in the other direction (unlike, for instance, current hospitalizations). For this reason, the trends in the stock and flow can only diverge when the trend in number of new cases is in decline while the number of total cases, necessarily, continues to rise. While this represents only one particular conceptual combination (rising stock, falling flow), we contend that it represents a key applied combination in the arena of public health. As evidenced by the COVID-19 pandemic, the rate of new cases can wax and wane in successive, irregular waves while always adding to the running total. The very moment at which the rate of increase in new cases stalls likely proves pivotal in determining whether the collective response follows an overconfident or reasonably cautious route. In these situations, we predict that viewing the data as a flow (number of new cases per day) will lead people to believe there is less risk than those viewing the same data as a stock (cumulative number of cases by day). Further, we predict that exactly these assessments of risk will inform behavior: If people perceive more risk from the current state of the pandemic, we expect them to be less likely to engage in behaviors guided by that risk, such as indoor dining, personal care appointments, visiting with others, and sending children back to school.

We test these hypotheses in the following preregistered experiment (https://aspredicted.org/y6pf7.pdf).[1] Materials, data, and analysis code are all hosted and publicly available on the Open Science Framework (https://osf.io/bvpck/). In the experiment, participants are shown data of COVID-19 cases as either a stock (cumulative number of cases) or a flow (number of new cases) and asked about their perceptions of risk and then about a number of behavioral intentions. We focus on two time periods: one in which the number of new cases (flow) is increasing and one in which the number of new cases (flow) is decreasing. In both cases, to reiterate, the total number of cases (stock) is increasing. We expect the same data to lead to different subjective appraisals of risk and intended behavior when the flow trend is decreasing (and the stock trend is increasing) yet similar judgments of both risk and behavior when both are increasing.

Method

Participants

We recruited 600 participants via Amazon Mechanical Turk (AMT) to participate in the experiment for monetary compensation ($.60). Four participants—identified by their AMT ID—began the survey twice, so we removed all observations from these AMT IDs

[1] Due to a miscommunication, the survey was launched after only two of the three authors had formally approved the preregistration via the portal. We had neither downloaded nor inspected any data at the time the remaining author formally approved the preregistration, but we note for transparency that the formal final preregistration approval was documented after data collection had begun.

from the data before analysis, leaving a final sample of 596 (median reported age = 37; percent identifying as: female = 50.3% and male = 49.0%; percent responding to whether they have had COVID-19: "yes" = 2.7% and "maybe" = 9.6%).

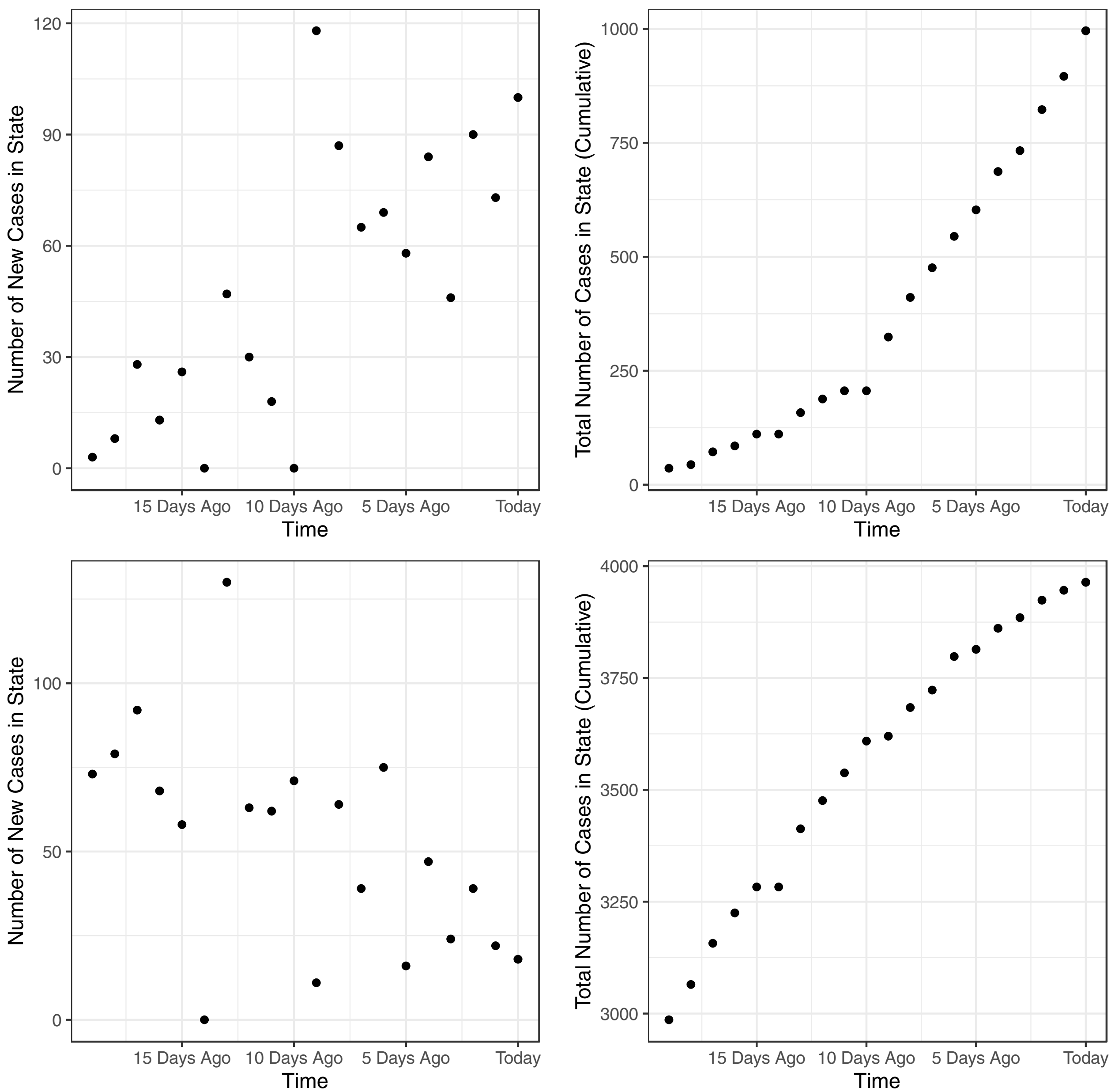
Design

Participants were randomly assigned to one condition in a 2 (presentation mode: stock vs. flow) × 2 (time period: flow increasing vs. flow decreasing) between-subject design.

Materials

Participants viewed 20 days of COVID-19 data from Oregon (U.S.). Based on condition, they either saw data from March 16, 2020 to April 4, 2020 (flow increasing) or May 7, 2020 to May 26, 2020 (flow decreasing) and these data were visualized as either cumulative number of cases (stock) or new cases (flow). Stimuli from all four conditions are shown in Figure 2. While the stimuli were constructed from actual COVID-19 data (retrieved from covidtracking.com), neither the state nor data range information was disclosed to participants (as described below).

Figure 2
Experimental Stimuli



Note. The top two panels are from the flow increasing condition and the bottom two panels are from the flow decreasing condition. The left two panels are from the flow condition and the right two panels are from the stock condition.

Procedure

The study was conducted online using Qualtrics survey software, augmented with Javascript. After consenting to participate in the study, participants were shown 20 days of COVID-19 data (stimuli dependent on condition). Participants were asked to imagine that "the following chart shows the [total (cumulative) numbers of cases]/[number of new cases] of coronavirus (COVID-19) that have occurred in your state" up to today. Participants in both conditions were also told the total number of cases (996 in the increasing flow condition, 3,964 in the decreasing flow condition) that had occurred up to "today" (since this information would not otherwise be available in the flow condition with only the most recent 20 days of new cases).

On the following two screens, participants were again shown the condition-specific visualization stimulus and responded to the dependent measures (see below). The order of the dependent measures was counterbalanced, and the behavioral intention dependent measures were all shown on the same screen. We found no effects of the counterbalancing factor, or its interactions with the focal factors, on either type of dependent measure (all *p*s > .19), so we will not discuss it further.

Finally, participants responded to six demographic and psychographic questions (described in Results section), were asked whether they had any comments or questions about the survey, and were thanked for their participation and paid.

Although all participants were asked to make judgments about the context presented in the stimuli and *not* the actual context on the current day, we note that the study was conducted on November 5, 2020. On this day, approximately 120,000 new cases of COVID-19 were reported in the United States and the number of new cases was trending upward.

Dependent Measures

Risk Perception

Participants were asked "Imagining that you are currently living in this state: What do you think the current level of risk is with respect to coronavirus (COVID-19)?" and responded on an 11-point scale anchored by *no risk at all*—0 and *serious risk*—10.

Behavioral Intentions

Participants were asked to imagine "you are currently living in this state" and were asked "How likely would you be to do the following things?" Participants responded to 13 items, each on a 7-point scale anchored by *extremely unlikely* and *extremely likely*: (a) "Dine indoors at a restaurant," (b) "Dine outdoors at a restaurant," (c) "Take public transit, a cab, or an Uber/Lyft," (d) "Invite a friend over to your house (and be indoors)," (e) "Accept an invitation to a friend's house (and be indoors)," (f) "Go shopping (indoors) for nonessential items (like new clothes)," (g) "Go to a gym or attend a workout class," (h) "Send an elementary school age child back to school (indoors and in person)," (i) "Plan a get together with friends/family over Thanksgiving," (j) "Visit a doctor for a routine checkup," (k) "Visit a dentist for a nonessential procedure," (l) "Visit a salon/barber to get your hair cut," and (m) "Stock up on food/toiletries/cleaning products." The 13 items were averaged to form a composite measure (with the 13th item reverse coded).

Results

Risk Perception

When shown data in which the number of new cases was decreasing (decreasing flow condition), we predicted participants would perceive greater risk when viewing those data as a stock (cumulative number of cases) versus a flow (number of new cases). We further predicted no difference between the presentation modes when the data had an increasing number of new cases, as both stock and flow presentations would have an increasing trend.

The results, shown in Figure 3, support these predictions. An ordinary least squares (OLS) regression predicting risk judgments using presentation mode (coded: stock = 1, flow = −1), time period (coded: increasing flow = 1, decreasing flow = −1), and their interaction revealed a significant interaction, $t(592) = -3.39$, $p < .001$. Planned contrasts revealed participants believed there to be less risk when viewing the flow (vs. stock) presentation in the decreasing flow condition, $M_{\text{stock}} = 6.58$ [$SD = 2.68$] versus $M_{\text{flow}} = 4.72$ [$SD = 2.34$], $t(592) = 6.25$, $p < .001$, Cohen's $d = 0.74$, and similar risk judgments when viewing the flow (vs. stock) presentation in the increasing flow condition, $M_{\text{stock}} = 6.91$ [$SD = 2.58$] versus $M_{\text{flow}} = 6.47$ [$SD = 2.58$], $t(592) = 1.48$, $p = .139$, Cohen's $d = 0.17$.

Behavioral Intentions

We predicted that behavioral intentions would follow risk judgments: People would report a greater likelihood of engaging in risky activities when risk perceptions were lower. Thus, we predicted a similar interaction as we observed for risk judgments (divergent intentions in the decreasing flow condition and similar intentions in the increasing flow condition).

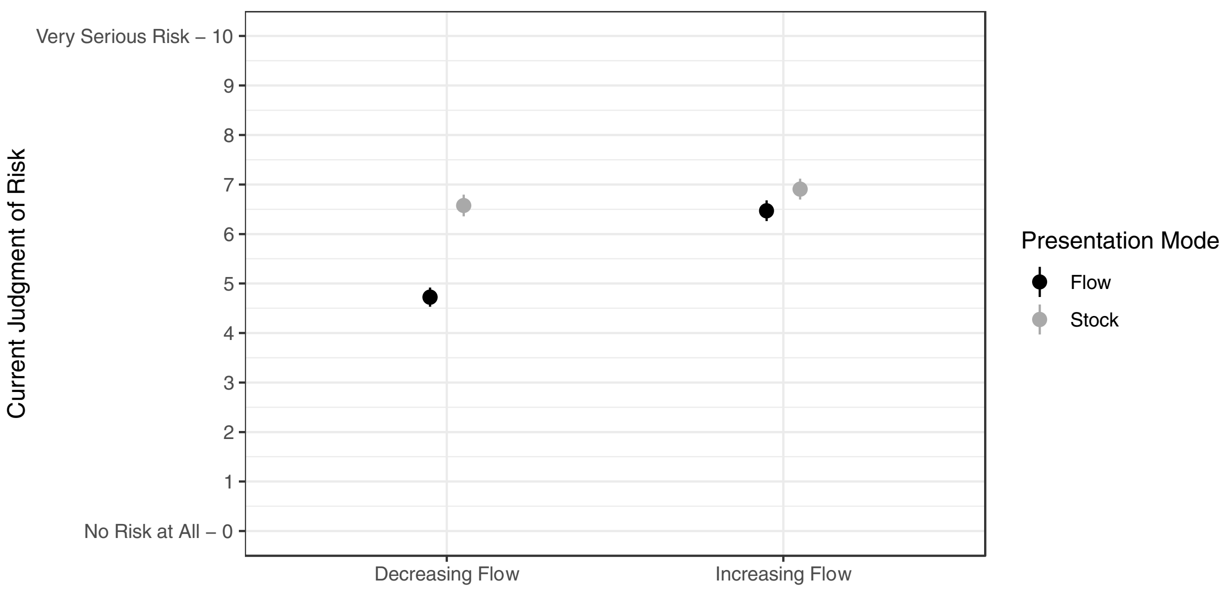
The data, shown in Figure 4, partially support our prediction; however, an unexpected result emerged. Using the same predictors in an OLS regression with the composite behavioral intention measure as the dependent variable yielded a nonsignificant interaction, $t(592) = 0.45$, $p = .65$, and two significant main effects: Participants indicated stronger intentions to engage in risky behavior in both flow presentation mode conditions (vs. stock presentation mode: $t(592) = -3.26$, $p = .001$) and in both decreasing flow time period conditions (vs. increasing flow time period: $t(592) = -3.10$, $p = .002$). For the interested reader, we show the results from each of the individual behavioral intention items in Figure A1.

The difference between the stock and flow presentations in the decreasing flow condition was predicted, $M_{\text{stock}} = 2.92$ [$SD = 1.42$] versus $M_{\text{flow}} = 3.36$ [$SD = 1.47$], $t(592) = -2.62$, $p = .009$, Cohen's $d = .30$. The difference between the stock and flow presentations in the increasing flow condition was not predicted, $M_{\text{stock}} = 2.61$ [$SD = 1.42$] versus $M_{\text{flow}} = 2.94$ [$SD = 1.45$], $t(592) = -1.99$, $p = .047$, Cohen's $d = 0.23$. We speculate on possible explanations for this unpredicted result in the General Discussion section.

Do Risk Judgments Predict Behavioral Intentions?

While it might be sufficient to assume that the types of behavioral intentions we measured (e.g., whether to dine indoors) should follow from judgments of COVID-19 risk, we sought to assess the degree to which the data were consistent with this link in two

Figure 3
Risk Judgments by Condition



Note. Error bars indicate the standard error within the condition.

ways. First, we assessed the simple (Pearson) correlation between risk judgments and behavioral intentions in our sample. We found a correlation of -0.496 ($p < .001$) indicating that risk judgments explained approximately 25% of the variation in behavioral intentions ($R^2 = 0.246$).

Second, we used a standard mediation approach (Baron & Kenny, 1986; Preacher & Hayes, 2004) to conduct an exploratory (i.e., not preregistered) analysis to determine whether risk judgments—as influenced by the presentation manipulation—mediated behavioral intentions. Using a bootstrap approach (e.g., Hayes, 2017),[2] we estimated an indirect effect of 0.094 with a 95% confidence interval that excluded zero [0.039, 0.153] suggesting that risk judgments, as induced by the manipulations, mediate behavioral intentions. In fact, out of the 10,000 bootstrapped sample, only 5 (0.05%) resulted in negative estimates. Controlling for risk judgments, there is no residual effect of the manipulations on behavioral intentions (the "direct paths," ps $> .19$), providing evidence for indirect only mediation (Hayes, 2017; Zhao et al., 2010). This suggests that the pattern of results is consistent with a causal model in which presentation format affected people's behavioral intentions because it changed perceptions of risk, albeit constrained by the typical caveats associated with drawing causal inference from mediation analysis (Fiedler et al., 2011).

In addition, the link in our data between risk judgments and behavioral intentions seems strong and robust. This link holds despite the fact that there are reasons where behavior might not follow risk perceptions, especially in the case of COVID-19. For example, some people may not fully appreciate the extent to which the risks they take can harm *other* people (i.e., prosocial concerns). Additionally, some people may not be able to reduce their exposure to risk (e.g., needing to take public transit to commute to an essential job). Still, our results suggest that data presentation format reliably shifts risk perceptions which, in turn, affect behavioral intentions.

The Influence of Demographic and Psychographic Factors

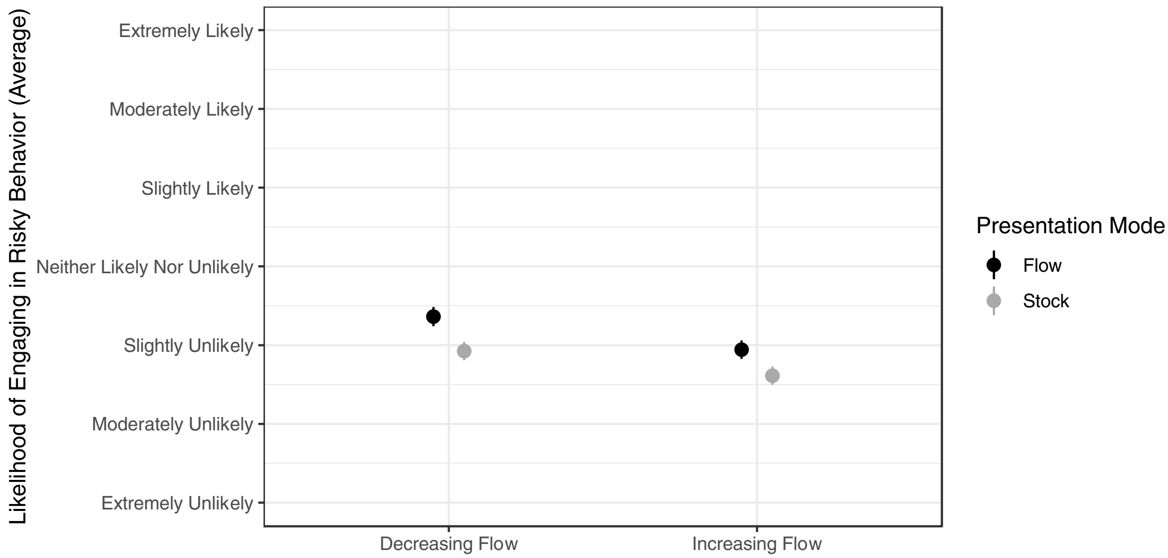
We asked participants to self-report six pieces of information we thought could influence their judgments of risk and/or behavioral intentions: age, gender, location (urban, suburban, rural, other), whether they have had COVID-19 (yes, maybe/not sure, no), whether they consider themselves "high risk" for negative outcomes resulting from COVID-19 (yes, no), and their political party association (strong Democratic, lean Democratic, neither, lean Republican, strong Republican). For each item, participants had the option of not responding.

To assess whether any of these factors moderated the interactive effect of presentation format (Presentation mode × Time period) on risk judgments, we ran separate regressions including each factor (individually) as a third predictor variable (continuous for age and political affiliation; categorical for gender, location, and the two COVID-19-specific questions). None of the three-way interactions reached a conventional level of significance (all ps $> .13$), suggesting that the interaction effect we document does not depend on these covariates.

Assessing the covariates individually (controlling for the Presentation mode × Time period interaction) yields two significant ($p < .05$) conclusions: People who self-report being high risk for COVID-19 complications report higher judgments of risk, $b = 1.04$, $t(573) = 4.42$, $p < .001$, and people who identify more strongly with the Republican Party report lower judgments of risk, $b = -0.44$,

[2] We sampled our data (with replacement) 10,000 times and conducted two regressions on each sample: the first predicting risk judgments using presentation mode, time period, and their interaction and the second predicting behavioral intentions using risk judgments and the three predictors from the first regression. We then multiplied the estimated interaction coefficient in the first regression and the risk judgment coefficient in the second regression within each sample yielding a distribution of indirect effect estimates that can be used to characterize the uncertainty of the estimate in the full sample.

Figure 4
Composite Behavioral Index by Condition



Note. Error bars indicate the standard error within the condition.

$t(585) = -5.79$, $p < .001$. Again, though, we find no evidence that either factor moderates the interaction of presentation format with flow trend on risk judgments.

General Discussion

Pandemic data are commonly presented as a time series of either new cases per day (flow) or the corresponding cumulative total number of cases at each day (stock). As of the time of this study, two of the most prominent data communicators defaulted to different presentation modes. At the top of its COVID-19 dashboard, the World Health Organization led with the number of new cases on that day (flow); users had to scroll down the page to see stock figures. Elsewhere, the Johns Hopkins Coronavirus Resource Center defaulted to cumulative stock cases in its reporting of the same data. Our experiment suggests that in certain circumstances—specifically, when the flow of new cases is decreasing while the stock of total cases is still increasing—the choice to present the data in one format versus the other can engender different levels of risk perception in the audience. Further, these risk judgments seem likely to influence whether people engage in certain types of behaviors that may increase viral transmission.

Accuracy of Judgments

As mentioned in the Introduction, the current investigation diverges from past work on *stock–flow failure* in that our separate focus on *stock–flow inconsistency* leaves us unable to draw conclusions about which presentation format leads to greater accuracy. Instead, what we are able to conclude is that the same data presented as a stock or a flow leads to *inconsistent* judgments of risk and behavioral intentions.

While we cannot make conclusions about accuracy, one might still wonder which presentation format leads to *better* judgments. While speculative, we believe that a case could be made for either format, depending on how one defines “better.” We contend that objectively, the flow-based presentation—number of new cases per day—makes the most diagnostic information more readily perceivable: The best proxy for true risk in infection data is probably some function of the number of new cases within the past (approximately) 2 weeks, as these cases are more indicative of current levels of transmission (unlike those that occurred—and got resolved—months ago, still lingering in cumulative stock). The flow presentation makes this information, in theory, easier to read. However, this potentially diagnostic information is shown by the magnitude of flow (the y-position of the data point), and our results suggest that it is—instead—the *trend* (slope) in the data that people utilize in making risk-related judgments (i.e., whether things are getting better or worse).

On the other hand, one could argue that better judgments in this particular case may be those that lead to the most socially beneficial behavioral intentions (i.e., lower likelihood of engaging in “risky” activities), particularly in the case of a pandemic, where negative externalities of risk taking can cascade exponentially. Research suggests that anti-contagion policies such as social distancing policies and business closures can greatly reduce the exponential spread of the virus (Hsiang et al., 2020) and substantial reductions in mobility could help bring the virus’ reproduction rate (R) below 1 (Nouvellet et al., 2021). Because stock presentation, in our data, led people to see more risk and to shy away from engaging in risky behaviors, one could argue that the stock-based presentation fosters better judgments about risk.

While many common activities that provide clear benefits involve some risk to both the actor and the broader community (e.g., driving a car), taking risks within a context of communicable disease can have particularly acute consequences to society at large. Accordingly, stock presentation might increase appropriate risk responses by ever so slightly shifting this omnipresent risk–reward calculus toward erring on the side of caution—though without seeking to *completely* eliminate these activities for both psychological reasons (e.g., the mental health benefits of seeing friends) or economic reasons (e.g., the continued success of local restaurants and retail shops).

Practical Recommendations and Ethical Considerations

The inconsistency in judgments we observe is problematic. Ideally, for a given set of data, there would be a neutral way to present it—an ersatz control condition—so that the facts could speak for themselves. However, this does not seem to be the case with time series data like pandemic infections. Inherent to visualizing the data is making a choice on how to present it (stocks vs. flows), and this choice will influence how the data are perceived and how judgments are made.

Rather than attempting to reduce these presentation-format-induced inconsistencies in judgments, understanding that—and how—the choice between presentation frames influences judgments can have immense pragmatic value. From the perspective that visualizations should serve a rhetorical purpose (Hullman & Diakopoulos, 2011), our results offer a tool: If a communicator wants people to perceive greater current risk, presenting cumulative case numbers seems the more persuasive approach (particularly when the number of new cases is trending downward). In this sense, we do not tackle the entrenched problem of *stock–flow failure* but instead leverage our results to offer a solution of sorts to an altogether different issue—how to induce people to perceive greater risk. In this way, our results lend credence to the possibility that presentation format may be akin to other types of behavioral nudges (Thaler & Sunstein, 2008). Moreover, the type of nudge we offer here is relatively cost free compared to some other proposals for "flattening the curve" (e.g., increasing testing). Further, it seems as if this type of nudge can act independently of other types of interventions—we do not see the effect we observe as competing with other means by which to reduce transmission during a pandemic. Thus, although the effect size of presentation format may be modest outside of the online laboratory, the return on investment may be quite favorable given the minimal cost (Benartzi et al., 2017).

We note, of course, that people tasked with presenting data to the public will likely have to grapple with ethical considerations in choosing a presentation format to advance their motives—even if those motives are to keep people safe. We feel that in this case, both presentation formats are equally valid from an information perspective. But, it is not clear if this removes the ethical burden from the presenter. The idea of choosing to present COVID-19 data as stocks to keep people safe might seem reasonable, but would the idea of choosing to present COVID-19 data as a flow to boost economic activity feel different? While high risk-appraisal likely keeps concern top of mind and case counts low, we also note that there are psychological costs to fear and psychological benefits to gathering and socializing.

To consumers of pandemic data, our advice is more straightforward: In the absence of an impartial data presentation format, look at the data both ways. Most websites have an option to toggle between formats. If nothing else, it might help boost one's understanding of accumulation data, which is relevant in many other domains (e.g., climate change; Cronin et al., 2009)—in turn underscoring the broad realm of other domains to which our results on risk and behavior might be brought to bear.

Limitations and Future Directions

A potential limitation of our study regards the stimuli. Using real data, we focused on two time periods that allowed for a test of our hypothesis: one period with an increasing flow trend and one period with a decreasing flow trend. This approach helps attest to the ecological validity and real-world implications of our investigation. Yet, real data come with idiosyncrasies, which may have influenced the observed results.

One potential concern is that, because we used real data, the number of total cases differed between the increasing (March 16, 2020–April 4, 2020) and decreasing scenarios (May 7, 2020–May 26, 2020). While this presents a possible confound, we think it is unlikely to have caused the interaction we observe for two reasons. First, we observe a large difference in risk perceptions between the stock and flow presentations *within* the decreasing scenario, even though the total number of cumulative cases was clearly shown to participants regardless of presentation format. Second, out of all four conditions, we observe the lowest level of risk perceptions with the flow presentation in the decreasing scenario (which had more total cases), which would not be consistent with participants perceiving the total number of cumulative cases as a diagnostic input.

We also chose to present the data using scatter plots (points), whereas these data are also frequently presented using bar charts (e.g., the examples from the CDC in Figure 1). While related work has suggested that these more esthetic visualization choices (e.g., dots vs. bars) are of limited consequence to translation success (i.e., *stock–flow failure*; Cronin et al., 2009) and downstream judgments (Spiller et al., 2020), we acknowledge that this remains untested in this specific context.

We also note that the results regarding behavioral intentions offered an unexpected finding: Although people reported similar judgments of risk for both presentation formats when the flow was increasing, behavioral intentions indicated greater risk-seeking behavior for those in the flow format condition (vs. the stock format condition). It remains possible that this is a spurious difference, but it is also possible that the internalization of risk-related information is likely one of many determinants of intended risk taking. Social norms, the behaviors of close others in one's network, and inferences about risk drawn from government-regulated closures (or the lack thereof) are likely strong inputs into decisions regarding discretionary activities. When such distinct inputs all align, they may jointly be stronger determinants of behavioral intentions. However, when people receive mixed messages from opinion leaders who advocate staying home but themselves travel and dine out, they may experience greater ambiguity regarding those activities, leaving a vacuum to be filled with one's own data-driven inferences.

Finally, we focused on two prominently used methods for communicating COVID-19 data: time series presentations of new confirmed cases (flow) and total confirmed cases (stock). To be sure, other metrics and presentation formats are not only possible but prominent—including those for which the time series element is de-emphasized. For example, *The New York Times* offered a heat map feature that attempts to communicate the level of risk directly, with more intense colors corresponding to higher risk. Similarly, Colorado used a color-coded system for communicating risks to its citizens (e.g., purple = extreme risk). We think these alternative metrics are promising, but could also be problematic as the mapping between these indicators and true risk is often opaque (e.g., “Can I walk with my friend outside if the risk level is ‘blue’?”). Additionally, they may suffer from the same relativity issues that seem to affect people’s judgments when viewing time series data (e.g., “Yesterday was ‘purple’ and today is ‘red,’ so things are getting better!”).

Conclusion

The present investigation leveraged the COVID-19 pandemic as an opportunity to ask theory-driven questions about presentation format, subjective risk, and downstream behavior in a manner that also carried clear applied relevance in providing practical answers to pressing questions in the midst of a public health emergency. Data on COVID-19 have been prevalent during the pandemic—specifically, time series presentations of new confirmed cases and total number of confirmed cases. Our results suggest that the choice between these two common data presentation formats can impact how people judge their present level of risk, specifically when the number of new cases is decreasing. A falling rate of new cases still indicates new transmissions. And while it might indicate a lower level of risk than the day before (depending on the number of contagious individuals), it does not imply a low level of risk in the absolute sense. Things can be getting better but still be far from good. Mistaking one for the other might too easily lead to a false sense of security.

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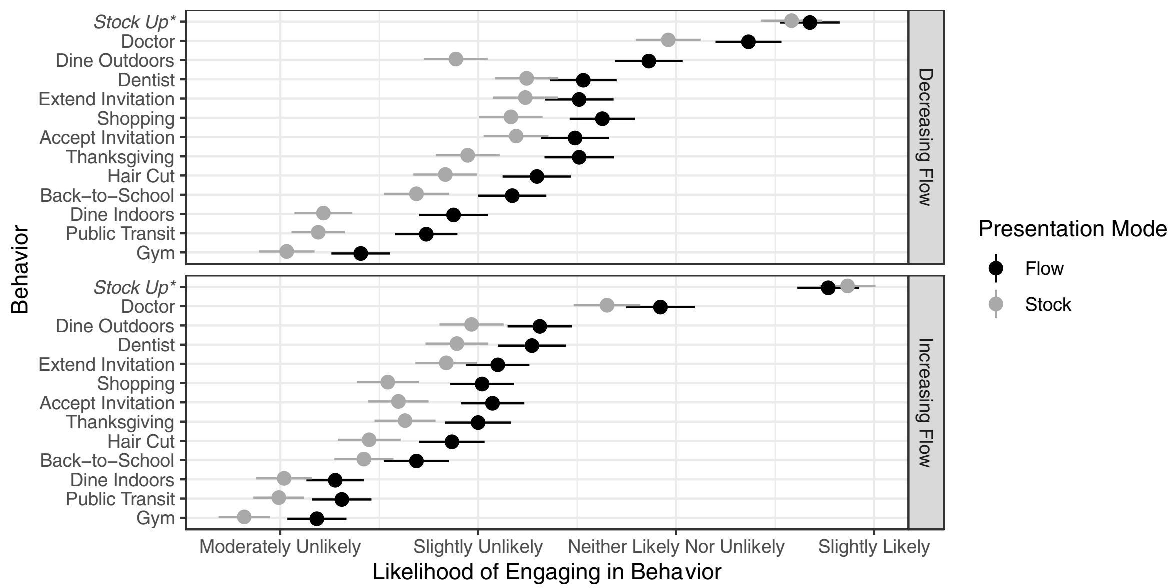
(*Appendix follows*)

Appendix

Figure A1
Behavioral Intentions for Each of the 13 Items



Note. Error bars indicate the standard error within the condition.

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