Commentary

Improving Measurement of Public Objective Knowledge About Hazards

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Attempts to measure objective knowledge (OK) of publics about hazards have been motivated by such questions as what do people know about the topic and why; whether and how such knowledge affects attitudes and behaviors regarding hazards; and whether a public information campaign changes knowledge or behaviors. These choices vary widely both within risk analysis and in related fields (e.g., science literacy; health literacy). The aim of this Perspective is to suggest that OK can be measured effectively if with several challenges, but that does not happen consistently, and even the best examples could be improved with several steps. After a brief review of variability in the literature in terms of how OK is defined and what outcomes it might be associated with, I review several challenges faced by OK measurement: knowledge sources, content salience, content timing, scale discrimination ability and dimensionality, and response options and scoring. Although the full suite of challenges is of concern, I focus particularly on novel hazards for which the scientific basis for much definition of "objective" knowledge is shifting rapidly, illustrated by the COVID-19 pandemic in the U.S. I conclude with several recommendations for addressing these challenges so that OK can be better measured, and thus theorists and risk communication practitioners can both better grasp when and how OK makes a difference in attitudes and behavior relevant to hazards.

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1. Introduction

Scholars and practitioners often want to know what the public knows about the world, including its hazards, and knowledge's relation to risk-related views and behavior. Often their focus is on how knowing "more" basic facts about physics, chemistry or biology, or specific technologies or issues shapes these responses, versus knowing "less," but knowledge also can include facts about how scientists work

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or their role in society (NASEM, 2016). There also has been rising interest in non-facts, so that an International Fact-Checking Network has promulgated a code of principles and best practices for fact checking organizations (NASEM, 2020; Poynter, 2022).

My focus on objective knowledge rather than on subjective knowledge or how much people *believe* they themselves know (e.g., in *Risk Analysis* see such examples as Siegrist & Cvetkovich, 2002; Martin et al., 2007; Malka et al., 2009; and Milfont, 2012; cf. Dunning, 2011 more generally), or personal experience, which some researchers define as knowledge (e.g., Mauro & McLachlan, 2008).[1] Rather, my focus here is on assessing whether and how what non-scientists believe is similar to what scientists and other experts believe about the universe, which is often labeled "objective knowledge" (OK) to indicate the presumed superiority of expert knowledge, and thus its validity as a standard against which to measure the quality of lay knowledge. Later I will briefly cover the strengths and weaknesses of this perspective, but for now the existence of OK will be presumed, which is rarely correlated with subjective knowledge (e.g., Baird, 1986; Costa-Font et al., 2008; Prati & Pietrantoni, 2016; cf. Dunning, 2011). I also exclude from my purview studies which measure OK—e.g., on nuclear energy use in space (Maharik & Fischhoff, 1993) or children's understanding of protective behaviors against various natural hazards (Yildiz et al., 2022)—without then determining OK's association with other beliefs, attitudes, or actions. These OK-only studies do not entail quite the same potential challenges or potential benefits as those of concern here. Further, my focus is on issues regarding OK measurement in large-sample surveys, as opposed to qualitative OK research (e.g., Strydhorst & Landrum, 2022). Such research can be very illuminating, including to develop survey measures, but poses somewhat different challenges and opportunities. As most OK research involves surveys, this limitation is reasonable.

I believe that the task of measuring lay objective knowledge in large-*n* surveys is more subtle and challenging than it seems to appear in much of the scientific literature. This is not a new critique (e.g., Johnson, 1993; Morgan et al., 2002), but those earlier arguments seem to have had little impact on OK practice . After laying out the rationales for and against measuring objective knowledge, including a partial review of salient literature, I cover several measurement challenges that have been hampering the field, including a few examples from the COVID-19 literature, and wrap up by summarizing my recommendations for making progress.

2. Why Measure Objective Knowledge?

The answer requires addressing three issues: 1) what is meant by "objective knowledge" (OK)?; 2) what effects could OK have?; and 3) how large might those effects be, especially controlling for other potential predictors? The "knowledge deficit" model (which appears under varied names: Cook & Overpeck, 2019) implicit in most OK measures—i.e., that knowing more about science and technology will yield more accurate attitudes toward them given the increasingly "scientific and technical" character of public policy (e.g., Pierce & Lovrich, 1982)—has been criticized by many scholars on grounds that empirical literature does not support such relationships (e.g., Wynne, 1992; Cook & Overpeck, 2019).[2] This claim is obscured by uncertainty over whether knowledge-deficit critics or defenders claim that knowledge is the only, or the only major, factor in attitudes and behaviors regarding science and technology, or one (perhaps weakly) of many, a question I cannot pursue here. Despite normative or other grounds for knowledge-deficit critiques, my focus here is solely the empirical data, which appear to yield mixed results.

Table 1 shows answers for the first two questions, and selected answers to the last. Including science literacy, health literacy, and risk analysis as pertinent disciplines, OK can cover diverse knowledge (first column) from general scientific facts from physics, chemistry, biology and other basic fields to understanding of systemic societal elements that affect health equity or science-as-an-institution. Risk analysis itself has emphasized "specific facts about a phenomenon, technology, or entity," so I have expanded that table section to detail how these kinds of OK measures have been applied (second column). Omitted from this table are two categories of the tripartite health literacy taxonomy proposed by Nutbeam (2000), as they are relevant but largely overlap with existing categories. Functional health literacy combines the specific-facts approach, and the protective-behavior (reduce risky, and increase healthy, behaviors) and risk communication (convey facts with comprehensible and linguistically appropriate, empathy-driven language) potential associations (Nutbeam, 2000; NASEM, 2021, 2022). Where functional health literacy goes beyond risk analysis applications is to urge complementing these elements with integrated health policies and services to assist patients in using such knowledge to develop "control, choice, collaboration, and consequences" regarding their health (NASEM, 2022, p. 5; see Chinn & McCarthy, 2013 for one attempt to measure all three health literacy concepts). Such complementary policy development does not appear explicitly in either risk science or risk practice, although occasional discussions of institutional trustworthiness, risk analysis ethics, or risk

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communication might implicitly raise the issue. Interactive health literacy, the ability to solve problems and make decisions with the understanding gained from health literacy (Nutbeam, 2000; NASEM, 2021), is included in the potential association of specific facts with behaviors, which in risk analysis has been exemplified by the mental models approach to risk communication (e.g., Morgan et al., 2002).

Type of Objective Knowledge	Potential Associations	Examples and Relationships
General facts about the universe (e.g., whether the sun circles the earth or vice versa; e.g., Miller, 1998)	General orientations or dispositions towards science and technology and its social impacts (Allum et al., 2004): e.g., its risks and benefits, its trustworthiness, resulting speed of societal change, whether it merits more government funding	Small but usually positive association across multiple datasets and domains (Allum et al., 2004)
Specific facts about a phenomenon, technology, or entity	Views on particular scientific issues or specific technological applications (Allum et al., 2004)	Small but usually positive association across multiple datasets and domains; domain-specific knowledge had much stronger association with domain-specific attitudes than did general textbook knowledge (Allum et al., 2004)
	Risk perceptions	"if . . . measured in a reliable and valid manner, the correlation between knowledge and perceived risks is strong across varied domains" (Siegrist & Árvai, 2020, p. 2194) OK of formal risk estimates and proposed standards unrelated to informal risk estimates (Baird, 1986) OK of heavy metal soil contamination uncorrelated with risk perception (Grasmück & Scholz, 2005) Reading a booklet which increased OK about cell phones raised concerns about cell phones, but decreased concerns about base stations, over two weeks (Cousin & Siegrist, 2010)

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Type of Objective Knowledge	Potential Associations	Examples and Relationships
		Ebola OK correlated negatively with Ebola risk perception and prejudice toward African immigrants (Prati & Pietrantoni, 2016) OK about chemicals in second-hand e-cigarette vapors, despite controls, raised risk perceptions (Tan et al., 2016) “Chemophobia” associated with OK of basic toxicology and chemical regulation (Saleh et al. 2019; cf. Kraus et al., 1992, and MacGregor et al., 1999) Zika OK correlated with perceived risk in a second sample, but less than did conspiracy beliefs in both samples (Piltch-Loeb et al., 2019)
	Risk acceptability	OK of formal risk estimates and proposed standards unrelated to risk tolerance (Baird, 1986) OK of irradiated food has small positive effect on acceptance (Bord & O’Connor, 1990). OK of heavy metal soil contamination uncorrelated with risk acceptance (Grasmück & Scholz, 2005) OK effects on support for animal and plant biotechnology mediated via trust (Knight, 2007) OK on radioactive waste and storage reduced support for nuclear power generation (Costa-Font et al., 2008)

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Type of Objective Knowledge	Potential Associations	Examples and Relationships
	Protective behaviors	Action-related OK increased, and result-related OK decreased, willingness to adjust behaviors affecting climate change (Shi et al., 2015) Of 12 risk-related communication materials developed in mental models research, only two measured effects on behavior rather than beliefs, but all reported positive effect for at least some outcomes (particularly on knowledge; Boase et al., 2017) OK enhances recruitment of representative samples of people for clinical trials (e.g., NASEM, 2020) Mental-models-based postcard increased wellwater testing in African-American communities doubled odds of self-reported water testing when combined with free test, and by 65% versus free test alone (Gibson et al., 2021) Demand for antibiotics predicted in part by antibiotic OK; willingness to prevent antibiotic use partly related to preventive OK (Visschers et al., 2021)
	Trust in hazard managers/stakeholders	OK of genetically modified foods increases trust (Zhu & Xie, 2015) Zika OK correlated with trust in government, but less than did

Type of Objective Knowledge	Potential Associations	Examples and Relationships
		conspiracy beliefs (Piltch-Loeb et al., 2019)
	Policy support	Causal OK increased climate change policy support; (Shi et al., 2015) Misconceptions about environmental problems (pollution and/or ozone depletion causes climate change) increases climate change policy support by 25% (Fleming et al., 2020).
	Develop risk communication efforts, and evaluate risk communication efficacy	Recreational fishing boat captains were generally aware of New Jersey fish consumption advisories, but had mixed accuracy and completeness in this OK, with varied relations to communication with their clients (Burger et al., 2003)
	Enhance science quality	Obtaining and understanding health information is critical for clinical issues from trial recruitment to compliance with medication and other instructions (NASEM, 2022, p. 5).
	Prevent or minimize rumor (e.g., Allport & Postman, 1947), misinformation and disinformation by supplementing fact-checking with understanding the who and why (e.g., political, financial, or reputational goals; affirmation of shared social identity; emotional triggering) of its spread (NASEM, 2020)	OK enhances people's ability to distinguish information, misinformation, and disinformation, and reduce online sharing of the latter two (e.g., NASEM, 2020), but it is unclear that the same OK increases both training and motivating
Critical health literacy: knowledge of root causes	Ability to identify and solve the community's health problems through systemic reform to	12 interventions to develop CHL mostly directed at youth, privileging cognitive

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Type of Objective Knowledge	Potential Associations	Examples and Relationships
and social determinants of local health problems (e.g., Nutbeam, 2000; NASEM, 2021)	build health equity (Sykes et al., 2013; NASEM, 2021, 2022)	skills development over social action; least effect on understanding of social determinants of health, constrained by inadequate CHL operationalization and institutional constraints (Sykes & Wills, 2019)
Facts about scientists, scientific process (e.g., Scientific Reasoning Scale [SRS]; Drummond & Fischhoff, 2015) scientific institutions, or science's relation to society		Methodological facts likely to have similar relationships as in general or topic-specific facts (Evans & Durant, 1995; Allum et al., 2004); little work on science's relation to society (Allum et al., 2004) Higher SRS associated with more selection of interests and value differences as explaining intra-science disputes regarding nanotechnology, but not regarding dietary salt intake (Dieckmann & Johnson, 2019) Convey uncertainty and changing data/ interpretations over time; COVID-19 science not just from pandemic itself, but decades of research on vaccines, viruses, and treatment (Strydhorst et al., 2022)

Table 1. Examples of Types of Objective Knowledge, Potential Associations with Various Outcomes, and Examples and Relationships Found in Empirical Research

Table 1 (third column) is not a full empirical literature review, as far beyond both available resources and Perspectives' purpose in this journal, but is based on a search in May 2022 for the term "knowledge" in papers in *Risk Analysis.* The examples provided show no effect of objective knowledge, indirect effects only, small but broad direct effects (as in the large dataset analyses of Allum et al., 2004), and larger effects. Most of these analyses controlled for other potential factors besides OK, so these are net OK conclusions. For example, one study found knowledge effects on nuclear power generation acceptance controlling for stronger political ideology effects (Costa-Font et al., 2008); causal knowledge significantly increased climate change concern and policy support despite cultural controls (Shi et al., 2015); and effects of causal misconceptions on climate change policy support persisted controlling for general knowledge, ideology and other factors (Fleming et al., 2020).

Enormous literatures cover varied and contingent associations between risk beliefs (including but not limited to "facts"), attitudes, physical and social environment conditions, and behaviors, including effects of social norms, trust in responsible authorities, cultural biases and emotions, among others (e.g., Cialdini et al., 1990; Peters & Slovic, 1996; Slovic, 1999; Kahan, 2012). If outcomes meaningful to us as researchers and practitioners are "explained" by other factors, why focus on objective knowledge?

Its merits will vary by one's research or practical goals, but should be rarely zero. First, empirical data (Table 1) suggest some OK effect of on parameters of interest, if variable in magnitude and covariance with other explanatory factors. This variability might reflect differences in OK measurement (Section 3) as much or more than differences in potential outcomes of OK. Furthermore, we should address interpretive differences, as when "shallow but broad" findings could lead knowledge-deficit critics to emphasize the "shallow" finding, while those believing that "knowledge matters" emphasize the "broad" finding (Allum et al., 2004, p. 51). Even in the voluminous pages of *Risk Analysis* the relatively few survey-based papers on risk perception, risk behaviors, and/or risk communication that have used OK measures limits our conclusions about OK's overall role.

Second, we should determine *under what conditions* OK is more or less important. The experience of experts of OK's importance in their own professional and non-working lives, and/or by desires to maintain the cognitive authority of science (e.g., Campbell, 1985; Collingridge & Reeve, 1986; Jasanoff & Wynne, 1998; Zehr, 2000; Stilgoe, 2007) might encourage an expert assumption that OK must change views or behaviors even for non-experts, whetherrelatively high knowledge has already been achieved (crystallized intelligence: experience or accumulated knowledge [Li et al., 2013] or is gained by explicit efforts to educate them.

Yet some potential outcomes should be more associated with OK than others. For example, the "mental models" approach to risk communication design (Morgan et al., 2002) finds quite strong OK-

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behavior relationships if done properly, despite its limitations.[3] This method entails assessing relevant scientific literature and/or in-depth interviews with experts to develop influence or causal path diagrams about how undesirable consequences stem from upstream choices or events; in-depth interviewing of citizens about their own causal beliefs; developing OK measures based on critical differences between citizen and expert understandings; surveying to identify distributions of correct, erroneous, and other beliefs in the population, as defined; using qualitative and quantitative results to develop a public education guide; and evaluating the guide's effects. Its creators posited that correction of erroneous notions of hazard development—e.g., through a message that radon does not "soak into" wallpaper and carpets, but improved ventilation can reduce indoor levels because radon is a radioactive gas (Atman et al., 1994)—can foster more effective protective behavior (i.e., adding a ventilation system to one's basement versus removing all wallpaper and carpets; Bostrom et al., 1994). This method can potentially avoid the (probably common) mistake among communicators of "educating" people on beliefs that are *widely* and *correctly* held by the population. Further, the influence diagram's identification of critical nodes—intervention here with a specific behavior or policy can prevent further development of undesirable consequences—could increase OK knowledge measures' efficiency in increasing protective, and reducing risky, behavior, because targeted to correct beliefs that make a large difference. However, even if fully and competently implemented the mental models approach might leave out critical factors. The Protective Action Decision Model (e.g., Lindell & Perry, 2012), for example, posits that intentions to enact or not protective behavior are the joint result of threat perceptions, perceived attributes of the protective action itself, and stakeholder perceptions (e.g., of their trustworthiness or role in managing hazards); such intentions along with unspecified facilitating or hindering factors determine whether people take protective action, engage in emotional reactions, or seek more information. Any of these factors may be based in part on objective information, but need not be. That said, if someone wants to reduce their risks, mental-model-based and similar OK-focused information can help identify which protective behaviors are effective, affordable, and otherwise appropriate for them.

By contrast, it seems less likely that general attitudes toward science should reflect objective knowledge, in part because most such studies have used OK measures regarding basic scientific facts about the world rather than on the arguably more salient facts about scientific method, science institutions, and science's impacts on society. The Allum et al. (2004) finding of "shallow but broad" effects for the former association might indicate a floor effect just as I've suggested a ceiling effect for

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mental models' association with protective behavior, assuming potentially confounding factors have been controlled.

Third, knowledge and its competitors/complements need not be just parallel exogenous or mediating variables. For example, demographic variables (e.g., education, gender) have often been included as covariates that influence relative knowledge, while controlling for cognitive ability's (using vocabulary as a proxy) effects on knowledge, plus on science knowledge and science attitudes, still yielded a persistent effect of OK on science attitudes (Protzko, 2020). Although longitudinal and experimental designs would better explore such causal relationships, well-designed cross-sectional studies could do a better job of assessing more complex relationships of trust with other presumed predictors of science, health and risk outcomes.

Fourth, we should not ignore potentially important practical implications, particularly that even small effect sizes for OK may still have large societal effects if they generalize. Further, many equally or more important factors (e.g., ideology/culture; institutional trustworthiness) may be much harder to fix, even if changing objective knowledge or its effects may not be easy (e.g., ideological and cultural drives can heighten polarization among the most highly knowledgeable; Kahan et al., 2012). A final practical implication has to do with evaluating public information campaigns, which often seek to alter people's knowledge and/or their presumedly causally subsequent behaviors. Omitting questions about OK before, during, and after these campaigns fails to accomplish a basic obligation to justify the spending of this time, money and expertise to taxpayers, donors, and shareholders.

3. Objective-Knowledge Measurement Challenges

Despite the value of OK measurement, and some impressive empirical research over 40 years or so in multiple fields, methodological choices highly variable in both quality and content have stalled progress. Here I describe available options, dealing in turn with knowledge sources, content salience, content timing, scale discrimination ability and dimensionality, and response options and scoring.

3.1. Knowledge Sources

Measuring objective knowledge presumes available and reliable source(s) of such knowledge, usually deemed to come from science, technology and other experts, but the nature of such knowledge varies considerably. If testing associations between basic scientific facts and general attitudes toward science, the scientific knowledge is so widely confirmed that it appears in middle school textbooks; mental-

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models research often uses information from college textbooks, but may include interviews with working experts with more cutting-edge understanding. Regarding COVID-19, different OK measures in February 28, 2020 surveys by McCormack et al. (2021; I confirmed this with its lead author) and in my own survey (*reference omitted*) relied entirely on quick reviews of then-available scholarly and media data on SARS-Cov-2 virus and COVID-19 disease, plus our respective experiences as researchers, as relevant experts were understandably too focused on understanding the looming pandemic to provide help at this early stage (there were then fewer than 50 confirmed cases of infection in the U.S.). Although Morgan et al. (2002) mention the possibility and need to address scientific uncertainty , I am unaware of any current published OK research—mental model-based or not—that assumes uncertainty of any kind, including disputes among experts (e.g., continuing debate over origins of the SARS-CoV-2 virus; e.g., Andersen et al., 2020; Wade, 2021; Worobey et al., 2022). The usual assumption is of a series of facts defined by scientific consensus as true or false; laypeople have high knowledge if they say correct items are true and incorrect items false; saying the reverse, or "don't know," indicates low knowledge. The assumption rests upon several problematic premises: e.g., 1) relevant expertise is easily identified; 2) experts do not disagree; 3) facts are unchanging over time, place, or society; and 4) facts' inter-relations are unchanging. Defining acceptable degrees of scientific agreement and how to identify consensus are themselves challenging (e.g., compare climate scientists' apparent consensus that contemporary climate change is human-caused ["97%"; Cook et al., 2016], used in risk communication experiments [e.g., van der Linden et al., 2019], to much lesser agreement on severity of ultimate impacts or which policies are preferable [Pearce et al., 2017a, b]). Nor is all relevant knowledge from natural science and engineering; other sources mightinclude social science and communication, or lay publics' expertise on constraints and opportunities in their own lives that may be critical.

3.2. Content Salience

Measures should embody *meaningful* understanding: there should be a clear rationale for how OK beliefs are or ought to be causally associated with risk perceptions, protective behavior, or policy support, for example, which also should be explained to their audiences or users. Merely probing whether people know X without explicit causal imputations holds no value for either theorists or risk communicators, yet rationales for OK scales' content are rarely given.[4]

But beyond the researcher-defined and explained relationship, we must ask whether holding a given belief, *as framed by the researcher*, allows people to make researcher-assumed inferences about

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appropriate downstream beliefs or behavior, and *not* make other, inappropriate, inferences. Without this inferential consequence, the initial belief cannot be interpreted as actionable knowledge. If multiple downstream beliefs or behaviors (including inaction or risky behavior, not just protective behavior) could derive from the initial belief, then adherence to the initial belief might or might not be necessary, but it is clearly insufficient under these conditions.

To illustrate this problem, consider the following sequence of possible OK statements (not necessarily optimally phrased):

1. The coronavirus can be carried in tiny particles or aerosols expelled from an infected person's nose or mouth into the surrounding air as the person breathes or talks.
2. Coronavirus-infected particles or aerosols can stay suspended in the air for minutes to hours, raising the likelihood that people passing by can breathe them in.
3. Coronavirus-infected particles or aerosols suspended in the air are much less likely to infect passersby who wear masks covering both nose and mouth at once.

All three statements are true, and to varying degrees might be associated on their own with intention to enact the protective behavior of mask-wearing, but the 1-2-3 sequence is not inevitable. Other protective pathways could include inference from #1 that aerosols could be borne much further than large droplets from sneezing or coughing from their source, warranting keeping far more than six feet from others or installing better indoor ventilation, or inference from #1 or #2 that wearing a mask oneself reduces potential infection of others. Non-protective paths might include someone who "knows" #2 but not #1, so wears a mask covering the mouth but not the nose even while intending to protect others, while someone else might "know" all three statements, but wear a mask improperly or not at all to signal objection to being told what to do about viral transmission. In short, one's agreement or disagreement with a specific true or false item might or might not determine actionable OK about the hazard, whether one accepts these items as "objective" or not.

However much has been done in practice for OK items to represent actionable knowledge, only in two cases do explanations seem to appear. Mental models' OK items ostensibly cover causal knowledge gaps between experts and citizens; e.g., to encourage African Americans to test their private wellwater, OK topics include how to get water tested, routes and health effects of contamination, belief in sensory detection of contaminants, and concerns about costs (Gibson et al., 2021). Shi et al. (2015) on climate change distinguished physical (e.g., the role of CO_2 as a greenhouse gas and its sources), causal (e.g.,

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anthropogenic versus natural variability, CO_2 and temperature trends), action-related (policy and personal actions in reducing CO_2 emissions), and result-related (expected climate changes over the next decades under business-as-usual) OK, and expected (e.g.) that only action-related knowledge would not affect climate change concern, because concern would logically precede action intentions.

Lack of explanation need not imply current content is inappropriate. Of risk analysis examples cited above and in Table 1, only one study did not specify the exact items used (Prati & Pietrantoni, 2016 just described theirs as covering "Ebola, its transmission routes, and treatment"). Others are at least plausible: e.g., with a dependent variable of e-cigarette second-hand vapor (SHV) risk perception, it seems reasonable to ask about whether SHV contains only water vapor, tar, or formaldehyde (Tan et al., 2016), although one might ask why other risk-related topics (e.g., perceived dose-response relationships) were omitted (e.g., Kraus et al., 1992; MacGregor et al., 1999; Saleh et al., 2019). At the other end of the scale, some items may only indirectly measure actionable knowledge, perhaps the thinking behind the otherwise odd probing of whether people know that nuclear power plants are powered by nuclear fission (as reviewed in Johnson, 1993). Measures of Zika knowledge in one study (infection can be asymptomatic; transmission can be through sexual activity; birth defects can be an outcome) seemed reasonably associated with perceived risk, but without explanation for linking them to other dependent variables (i.e., trust in government, perceived control or self-efficacy, conspiracy beliefs; Piltch-Loeb et al., 2019). It is also unclear why acceptance of nuclear power generation should be associated solely with OK items on radioactive waste and storage (Costa-Font et al., 2008).

A different salience arises from risk communication evaluation. For example, McCormack et al.'s (2021, p. 108) objective was "to help inform health communications campaigns," hoping their results could serve as a baseline for tracking likely changes in knowledge levels despite their cross-sectional research design. Sometimes different groups evaluate public knowledge (e.g., public health scholars) and launch communication campaigns (e.g., public health agencies) without coordinating so the latter's effects can be evaluated effectively (as noted above on the two COVID-19 surveys in February 2020, this was a failure of feasibility, not unwillingness, to coordinate). Without coordination, OK measures may not be salient for the content of those campaigns. Sometimes timing and/or money for coordination fail, and often insufficient thought goes into campaign and evaluation goals, separately and jointly (e.g., see Bostrom et al., 1994's Section 3.2 on USEPA radon evaluation questions).

Our focus on salient content in OK measures should not overlook content of allegedly dependent variables either. For example, the generality of general science attitude measures provides insufficient

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common focus for respondents' answers, with the resulting conceptually "fuzzy" results not fully offset by the construct validity of the scale overall (Allum et al., 2008).

Finally, conceptual matching must be integrated with avoidance of common design errors (Bostrom, 1990, pp. 57-58, 71). If OK items are to identify misconceptions beyond those imagined by their creators), they must avoid 1) illusory discrimination, when inconsistent beliefs are impossible to express (e.g., the question and/or available answers are too vague to highlight those answers' inconsistency); 2) illusory expertise, when wording forces expression of answers reflecting expert beliefs that convey more information than intended by the respondent; and 3) reactance, with clues in the wording or structure of the knowledge item to the correct answer. Bostrom's (1990) analysis of two radon knowledge scales (Smith et al., 1987; Desvousges et al., 1988) found most items featured one or more such errors; it is likely similar criticisms could be made of other topics' OK items.

3.3. Content Timing[5]

I separate discussion of timing from other content salience issues given its import for uncertainty in what counts as OK, highlighted for COVID-19. On December 31, 2019 health officials in Wuhan, China reported a cluster of unknown-pneumonia cases; on January 30, 2020 the World Health Organization (WHO) declared the outbreak driven by this novel coronavirus (SARS-CoV-2) a Public Health Emergency of International Concern; on February 28, when the two surveys mentioned earlier launched, the U.S. Centers for Disease Prevention and Control (CDC) announced the first non-travel-related human-to-human transmission in the U.S.; two weeks later (March 11, 2020) WHO declared the outbreak a pandemic (Kupferschmidt, 2020b). This pandemic presented scientists with enormous challenges and opportunities, including sequencing viral DNA, developing testing tools and protocols, designing vaccines, modeling potential transmission and infection scenarios, and specifying protective behaviors and policies. Citizens were inundated with information, misinformation, and disinformation about the evolving science and technology, policymakers' claims and policies, health care workers' difficulties, supply chain problems, and ordinary citizens' claims and behaviors (e.g., Roozenbeek et al., 2020). They had to decide whether and how to process all of this, including any objective knowledge they might have or gain, exemplifying the poorly-labeled "midinformation" situation, which entails "informational ambiguity based on scant knowledge or emerging scientific evidence" (NASEM, 2020).

If expert consensus differs across time, an OK item's truth status also may vary. For example, my OK items included four on viral transmission—asymptomaticity; through such routes as feces and urine,

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touching surfaces, and sneezing and coughing—all technically correct in February 2020 when the survey launched, but that did not persist. Asymptomatic transmission was recognized early by scientists (e.g., Prather et al., 2020b). The virus occurs in human waste, as documented in wastewater tests—but human-human transmission via this route seems unlikely though not impossible, and can be controlled through effective hand-washing (e.g. Cuicchi et al., 2021; Mohan et al., 2021; Wong et al., 2020). Touching surfaces (counters, doorknobs, packaging, etc.) is a transmission route that initially prompted recommendations for regular cleaning, but experts eventually deemed it low-risk (e.g., infection risk of 5 in 10,000 or less; e.g., Harvey et al., 2021; Wilson et al., 2021). Although large droplets ejected during coughing and sneezing certainly transmit the virus, it took months for scientists, much less policymakers, to confirm that aerosols were more dangerous transmitters than droplets, as they remain suspended in the air for many seconds to hours, are most concentrated near the infected person but can travel more than two meters and concentrate in poorly ventilated indoor air, and are released far more by infected people than are droplets (e.g., Prather et al., 2020a). Neither this OK scale nor that of McCormack et al. (2021), both launched in late February 2020, featured an aerosols item. Aside from that omission, the phrasing of transmission (and other) items in both scales did not include absolute or relative risk qualifiers, so that a respondent could correctly say that all these items were correct without indicating understanding of their relative truth at any point in time. Delaying launch of OK items and the rest of the survey to better confirm expert knowledge limits potential benefits, while recommendations (Section 4) only partly ameliorate the timing problem. The binary assumption in most OK studies (noted above) precludes adjustment for changing expert knowledge; some minor steps could be taken with response scale design (Section 3.5).

Another timing issue is that OK's associations with outcomes might differ across time due to evolution of either the issue or scientific understanding of it. For example, Zika knowledge was associated with several beliefs and attitudes only after (versus before) local transmission through mosquito bites began in the mainland U.S., prompting the suggestion that knowledge differences "may only emerge as more information becomes available during the course of the outbreak or health information seeking" (Piltch-Loeb et al., 2019).

3.4. Scale Discrimination Ability and Dimensionality

Here the concern involves two issues raised by dominant multi-item OK scales: whether OK items maximize discrimination across differing knowledge levels, and whether OK is uni- or multi-

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dimensional.

General scientific literacy measures have been criticized as having too many easy answers to discriminate between high- and medium-knowledge, versus low- versus higher-knowledge, respondents (Pardo & Calvo, 2004), but this is a wider potential problem. Few studies appear to have assessed how much OK items distinguish high from medium from low knowledge. Assuming we only care about how people with minimal knowledge compare to those with some knowledge discounts actual variations in lay knowledge. Item response theory relates knowledge item and individual characteristics to the probability of correctly answering specific items (e.g., Embretson & Reise, 2000). Its various methods—e.g., Rasch (1960) for parametric and Mokken (1971) for non-parametric analyses—can probe items' relative difficulty (Schuur, 2003), allowing selection of scale items to probe for non-linearity in OK's relationship with presumed dependent variables.

Theorists and researchers seemingly believe that OK is uni-dimensional, given that this attribute is almost never discussed, despite most OK scales' item heterogeneity. Further, when dimensionality is mentioned, the focus is usually on reporting scale reliability using Cronbach's alpha (e.g., Pardo & Calvo, 2004 on low reliability of some measures), despite reliability statistics measuring internal scale consistency, not the scale's dimensionality, and Cronbach's alpha being an outdated and incomplete consistency measure (e.g., Johnson & Swedlow, 2022). To assess dimensionality, researchers must conduct factor analysis *before* reliability analysis. For example, Protzko (2020) found general scientific literacy items neither formed a unidimensional scale nor equally reflected the underlying OK construct; dropping three items (father's gene decides sex of baby; how long the earth goes around the sun; the center of earth is very hot) met these criteria and improved model fit. My own OK scale exhibited some variation in factoring across time (6 waves), but in general revealed only three somewhat-persistent subscales out of the 14 items used in all waves (also covering origins, vulnerability, and other prevention options), on transmission (3 items), mask efficacy (2 items), and severity (2 items). What is surprising is not the heterogeneity revealed by factoring, but the failure in most OK studies to probe likely multi-dimensionality given the heterogeneity of *their* OK items.

3.5. Response Options and Scoring

Most OK studies use a true/false or correct/incorrect response scale for each item (where a "don't know" option is included, or even more rarely an ordinal scale [e.g., Bostrom et al., 1994], most scoring is still binary), and then add people's scores across items to determine overall knowledge (e.g., McCormack et al., 2021 on COVID-19); sometimes scores are averaged. If each correct response yields one point, a 13-item scale yields overall scores of 0-13.

True/false scoring, and treating "don't know" responses as errors, is problematic when expert knowledge is itself uncertain or evolving. While more justified when more established scientific understandings are covered, items so simple that this absolute scoring works may insufficiently discriminate among different OK levels (Section 3.4). Bostrom's (1990) ordinal response scale allowed for mixed responses--"true," "maybe true," "don't know," "maybe false," "false"—and its use at least twice (Fleming et al., 2020; my survey) may allow other responses than "true" or "false" to be scored correct, but this complicates assessment of both expert knowledge and of OK in surveys.

Summing also has its problems. Multiple possible inferences from a given premise (Section 3.1), or multi-dimensionality of OK scales (Section 3.4), both make summing misleading .If the aim is to assess overall efficacy of risk communication campaigns, summing might be marginally appropriate, but will miss *which* topics gain in public understanding.

4. Recommendations

Table 2 summarizes some earlier points, while adding and justifying other suggestions that may improve when and how scholars and practitioners deploy objective knowledge (OK) measures.

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Recommendations	Explanations
Ensure choices among potential knowledge sources are not too narrow, and identify degree of consensus among sources	Even narrow topics may have multiple relevant scientific disciplines or sub-fields, and expertise from non-STEM fields may be relevant in certain cases. Grasp of consensus will inform both choice of specific OK items and of response options.
Consider multiple potential outcomes with which to associate OK items	This will be more pertinent to researchers with general versus narrower goals (e.g., to evaluate public information campaigns), but will build collective understanding of when and how OK has effects.
Choose OK sub-topics in the context of appropriate decision analysis	Use decision analysis or related methods to identify all factors supporting good decisions (e.g., Fischhoff, 1987; Furby et al., 1989). Such contextual work also may help on potential challenges of multiple inferences from a given premise (Section 3.2) or of items technically all true (or false) but to a varying degree (Section 3.3).
Match general content of OK items to presumed outcomes, including use of influence diagrams or other structured approaches, and explain this relation to your audiences	In mental models work (Morgan et al., 2002) influence diagrams identify critical nodes (i.e., intervening with a specific behavior or policy can stop undesired outcomes), for which correct beliefs greatly increase OK measures' efficiency. Influence diagrams' efficacy for other outcomes where causality may not be obvious or the only salient criterion—e.g., general attitudes on science, risk perceptions, or policy support—is unclear, but qualitative matching and explanation should be a minimum expectation.
Account for timing problem entailed by OK measurement of novel issues by prior design and testing of sample OK items	No preset OK items will address all novel topic OK completely, but can reduce timing problems. Infectious diseases as a class—e.g., Ebola, Zika, and COVID-19—vary widely in agents (e.g., bacteria, viruses), vectors (e.g., other humans, insects, arachnids, birds, animals), transmission routes (e.g., bodily fluids [semen, blood], large droplets from sneezing or coughing, aerosols, mother to in-utero child, touching contaminated surfaces, etc.), infective periods (e.g., symptomatic versus asymptomatic; duration), and other factors. Yet these shared *categories of attributes* allow generating conceptual associations and a consensual set of all-infectious-disease OK items across these variant category members *before* the next epidemic, from which researchers can select and edit for the infectious disease of the moment. Other hazard types require different taxonomies of causal pathways and OK items, and likely feature more within-class variability, but would still reduce need to devise OK scales for novel issues completely from scratch.

Recommendations	Explanations
Develop standardized concepts and measures of both OK and hypothesized OK outcomes as much as feasible, and if possible measure them at multiple time points	Varying project goals and resources, and researcher autonomy, will always yield variability in OK survey measures, but the more comparability achieved the more we will build knowledge of what people know, how these are related to potential outcomes, and how these patterns might change over time for both scholars' and practitioners' respective goals.
Address logistical burdens and barriers	OK appears in surprisingly few risk analysis publications, and the full mental models approach has been rarely implemented (e.g., Boase et al., 2017) given how long it takes to properly develop and test its various steps toward risk messaging. Besides bolstering efficiency and completeness of mental models applications (Bostrom, 1990), and taxonomic OK-scale development proposed above, funders, researchers, and practitioners must discuss and fund needed conceptual development and practice.
Apply item response theory to identify how much OK items discriminate among levels of overall knowledge, factor analyze OK items to identify their dimensionality, and use proper reliability measures for OK scales	These should be standard practice in OK and other survey topics, whether researchers are using standardized or *ad hoc* items.
Include response scales reflecting the degree of knowledge held by both expert knowledge sources and survey respondents, and use summary scores on multiple-item scales as only one analytical method	Assumptions that objective knowledge can only be true or false (as opposed to, say, "maybe true"), and that total knowledge is the only warranted endpoint, have hampered OK progress for reasons detailed in Section 3.5, as well as the likely multi-dimensionality of most if not all multi-item OK scales.

Table 2. Recommendations

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5. Conclusions

The potential benefit of OK measurement for risk analysis and other fields will be unlikely to diminish any time soon, as illustrated by the varying behavioral responses to COVID-19 and epidemiologists' expectation of a continuing trend of one or two novel human viruses annually (Woolhouse et al., 2008). My aim in this Perspective has been to advance the quality of research on objective knowledge's association with varied outcomes (both absolutely, and relative to other factors such as emotions, trust, and culture) by both acknowledging progress already made and recommending steps to address long-standing weaknesses in both conceptual and methodological choices. This improvement would in turn help advance risk analysis more generally—e.g., understanding of risk perceptions, protective and risky behavior, and policy support, and effective education of and policy discussions with citizens—as well as such other fields as science literacy and health literacy. I hope my colleagues will join me in implementing these advances.

Footnotes

[1] Experience might yield knowledge, but its enduringly ambiguous status as a factor in risk perceptions and protective behavior (e.g., Barnett & Breakwell, 2001; Bronfman et al., 2020; Knuth et al., 2014) underlines its highly contingent relation with knowledge.

[2] The notion of a gap in citizen understandings solvable by information transfer ("just the facts") occurs relatively early in Fischhoff's (1995) hypothetical stages of risk communication; he concludes that "the facts" are part, but only part, of effective and equitable risk communication.

[3] Its implementation often falls short (e.g., an influence diagram of flooding omitted spread of impermeable surfaces in a watershed as a factor [Lave & Lave, 1991]; Boase et al., 2017 found that of over 100 such studies in peer-reviewed articles published through February 2014, only 12 included testing of a risk communication message, only five used a randomized design, and varied widely in controls and outcomes included), its decision-analytic focus ignores some potential communication goals, and its assumptions are not always viable (Johnson, 2002 reviewing the Morgan et al. book). However, it gives us a far better tool for generating *some* appropriate OK measures than anything else available.

[4] Another issue beyond my scope here is whether alleged facts are distinct from beliefs generally (e.g., on hazard causes, how risky is X, etc.). For example, Americans' knowledge of basic science on human evolution and the "big bang" origin of the universe was long measured (and deplored) without qualms

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using items phrased as for other topics (e.g., whether the earth has a molten core). But experiments found knowledge improved considerably if these two questions were prefaced by "According to scientists. . . " or similar phrases, otherwise responses to these items reflected (dis)belief in human evolution and/or Young Earth religious belief (e.g., Roos, 2014; Weisberg et al., 2018). However, these distinctions are themselves potentially controversial and socially constructed: e.g., understanding that scientists believe X but disbelieving X oneself may make it impossible to apply interactive literacy if belief in X is necessary to solve a particular problem.

[5] Besides variability in timing, variability across societies (or poor cross-cultural equivalence) may be a problem in some cases (e.g., Peters, 2000; Pardo & Calvo, 2004), although Allum et al. (2008) found societal variation contributed only 10% to explained variance in general attitudes towards science and technology, despite a higher knowledge-attitude correlation in the U.S. than predicted. Given the assumed universality of at least basic scientific findings, this might reflect inattention to the wider social context (e.g., see evolution/Big Bang examples in note 4).

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