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A longitudinal analysis of usage patterns, topics, and information dissemination related to five names for cultured meat on social media

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ABSTRACT

Cultured-meat products, which have been hailed for their potential to address multiple drawbacks of traditional meat production, have received regulatory approval in countries including Singapore and the United States and are experiencing rapid market growth. The name of any product could influence public perceptions of it, and thereby affect consumption; and how cultured-meat products should be labeled remains the subject of debate. However, conducting large-scale consumer tests aimed at understanding the association between public perceptions of such products and the various proposed labels/names for them would be time-consuming and expensive. Therefore, this longitudinal research project on how five common cultured-meat labels have been used, and the associations between particular labels and public perceptions, instead relied on 424,382 relevant messages posted or retweeted on Twitter/X between July 2010 and December 2022. This novel approach enabled us to identify a dynamic interplay between label choice and public perceptions, and that each label was associated with a unique set of topics. Also, using social-network analysis, we were able to delineate the structures of cultured meat-related retweet networks and identify the key influencers within them. Our analysis revealed the importance of labeling within the challenging process of arriving at a consensus about what cultured meat should be called.

1. Introduction

Cultured meat is produced by culturing cells obtained non-lethally from an animal source (Gruber, 2022). It is increasingly seen as a potential solution to the animal-welfare harms and environmental damage associated with traditional meat production (Post et al., 2020). Singapore became the first country to approve the sale of cultured-meat products, from Good Meat, in December 2020 (Reuters, 2020); and the United States Food and Drug Administration (FDA) followed suit in the case of two companies, Upside Foods and Good Meat, in November 2022 and March 2023, respectively (CISION, 2022; GOOD Meat, 2023). In January 2024, Israel approved Aleph Farms to sell cultured meat based on beef (Staff and Wrobel, 2024), and in July 2024, Meatly announced that it had received regulatory clearance in the United Kingdom to sell cultured-meat products for use in pet foods (Meatly, 2024). Yet, despite these regulatory milestones and increasing investment, the cultured-meat industry faces a number of challenges, including technical obstacles to scaling up production (Ye et al., 2022); legislative hurdles (e.g., Arizona State Legislature, 2024; Office of Governor Ron DeSantis, 2024); and public concerns about the naturalness and safety of its products (Grasso et al., 2019; Pakseresht et al., 2022; Valente et al., 2019). As consumer perceptions of novel foods could influence their future acceptance (Jin et al., 2022), understanding and addressing such concerns is vital to the cultured-meat industry's growth.

Previous research has reported that unfamiliarity with new technologies does not prevent people from forming opinions about them. Indeed, the mere name of a technology can be decisive in the formation of attitudes about it (Anderson et al., 2013). However, debates about how cultured meat should be labeled are ongoing. Names proposed for it to date, hereafter referred to as labels, have included "clean meat", "cultivated meat", "cell-based meat", "lab-grown meat", "in-vitro meat", and "animal-free meat" (Choudhury et al., 2020; Ng et al., 2021), and this diversity reflects underlying differences of opinion. While advocates of cultured meat favor labels like "clean meat" and "slaughter-free

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meat", traditional meat producers may view them as disparaging to their products (Greene and Angadjivand, 2018). Additionally, consumers appear to prefer "lab-grown meat" and "synthetic meat" because they perceive these labels as differentiating these products from traditional meat more clearly than alternatives like "clean meat" (Greene and Angadjivand, 2018; Ong et al., 2020). To ensure accurate labeling of cultured-meat products, regulatory agencies are actively soliciting public opinion on naming conventions (FDA, 2021; U.S. Department of Agriculture [USDA], 2021). Nevertheless, no consensus has been reached about a label that balances the perspectives of different stakeholders and adequately informs consumers.

Against this backdrop, it is imperative to better understand how labels are linked to public perceptions. The existence of some such linkage is well established (Asioli et al., 2022; Bryant and Barnett, 2019; Hallman and Hallman, 2020; Verbeke et al., 2021), but most of the relevant studies have relied on survey experiments. Those studies have often had relatively small numbers of participants (e.g., Bryant and Barnett, 2019; Verbeke et al., 2021), raising questions about their external validity; and their reliability could be affected by factors related to respondent honesty and accuracy (Chen and Zhang, 2022). Moreover, while such methodological approaches may be invaluable for understanding initial public reactions to different labels, they could be limited by their relatively high financial and time costs, particularly when conducted longitudinally (Greenhoot and Dowsett, 2012; Scherpenzeel, 2018). Therefore, to develop a comprehensive and unbiased understanding of how different labels influence public perceptions, real-world data encompassing a wider and more diverse population should be analyzed.

Social media platforms' popularity with companies and individuals makes them useful to consumers wishing to learn and/or express opinions about novel food products and technologies. As such, these platforms are a rich source of longitudinal data and direct, as opposed to self-reported, insights into consumer opinion (Bifet et al., 2011). Among social media platforms, Twitter/X stands out as one of the most popular: with more than 500 million public messages, known as tweets, posted daily (Ying, 2023). Unsurprisingly, it is highly favored by researchers across various disciplines for investigating a broad spectrum of research problems (Thakur et al., 2023). Within the realm of food studies, for example, scholars have performed text analysis of Twitter/X data to gain insights into public opinion on various products including genetically modified organisms (Jun et al., 2020), eggs (Sass et al., 2020), and turmeric (Feldmeyer and Johnson, 2022). These dynamic data also represent a powerful tool for researchers' identification of trends and levels of public interest in various topics. For example, analyzing tweet volume facilitates not only broad measurement of changes in interest, attention, and engagement, but also the identification of key moments in such changes, as marked by notable surges and troughs in relevant Twitter/X activity (Kim et al., 2013). Most importantly, for our purposes, the frequency of certain labels in Twitter/X discourse may reflect the preferences of the platform's users towards those labels (e.g., Chew and Eysenbach, 2010).

Twitter/X enables its users to engage in interactions and collectively discuss shared topics, "follow" other users, and engage with their content through retweets, likes, and replies (Gabielkov et al., 2014; Moukarzel et al., 2021; Zhang et al., 2019). However, Kwak et al. (2010) highlighted that 77.9% of Twitter/X-user pairs linked in any manner had one-way connections only. This non-reciprocal nature of information-sharing enables certain influential users to shape the flow of information; and in the years since Kwak et al. wrote, the impact of these influencers' activities on other platform users' understandings, intentions, and behaviors has been further amplified (Moukarzel et al., 2021). Importantly, influencers in a network play key roles not only in their own communities, but outside of them (Himelboim et al., 2014). Among Twitter/X's interaction mechanisms, "retweeting" is arguably the most vital to information dissemination, as it allows rapid and easy propagation of content to a wide audience (Genes et al., 2014). By the same token, researchers can identify the main influencers within a network by analyzing retweeting activities (e.g., Bodrunova et al., 2016).

Few studies have hitherto utilized Twitter/X data to gauge public discourse on cultured meat. In one of them, Specht et al. (2020) manually examined 3,114 cultured meat-related tweets posted in the United States from August 2018 to January 2019, as part of an investigation of online discourse around cultured meat and its key influencers. In another, Pilařová et al. (2022) identified 36,356 cultured meat-related tweets posted from 2005 to mid-2022 using the keywords "cultured meat", "cultivated meat", "cellbased meat", and "cell-based meat" along with corresponding hashtags, and employed topic modeling and hashtag analysis to pinpoint the key characteristics and dominant themes of the discussions in which those tweets were embedded. And most recently, Kouarfaté and Durif (2023) collected 23,020 Twitter/X posts and 38,531 Twitter/X comments about cultured meat dating from January 1 to September 30, 2022, and used content analysis and statistical analysis to ascertain how media framing affected consumer attitudes. However, each of these studies captured cultured-meat labels via just one or two multi-keyword queries. They did not then separate the results by label, but rather analyzed these tweets as a whole, which might have limited their ability to provide in-depth, label-specific insights. Additionally, given the evolving nature of public perceptions towards new food technologies (Frewer, 2003; Singla and Sit, 2021), a longitudinal analysis with a larger dataset could provide valuable perspectives.

Accordingly, we conducted volume analysis, word-cloud analysis, and social-network analysis (SNA) of a 12.5-year longitudinal dataset of more than 400,000 tweets posted from July 2010 to December 2022, with the aims of identifying 1) dynamic changes in the usage patterns of different labels for cultured meat; 2) the evolution of the topics and themes of public Twitter/X conversations about cultured meat; 3) the key influencers in the dissemination of cultured meat-related information on Twitter/X and their label-adoption patterns; and 4) the evolution of cultured-meat information's retweet-network structure. The contributions of the current study are threefold. First, uniquely, it comprehensively maps long-term public perceptions about cultured meat, and changes thereto, associated with different label usages. Second, the multi-methodological approaches it uses to examine public discourses about cultured meat could serve as reference strategies for future research on public opinion about emerging food technologies using user-generated content. Third, its findings provide practical insights for key stakeholders such as cultured-meat companies and regulatory agencies on how to choose appropriate labels for communications.

2. Methods

2.1. Data collection and pre-processing

Following Huang et al. (2022) and Zhou et al. (2023), we used Brandwatch, 2023, a popular analytics platform that provides access to an extensive range of online sources, to collect 424,382 English-language tweets posted between July 1, 2010, and December 31, 2022. The keywords we used to collect these tweets included the phrases "lab grown meat", "cultured meat", "cultivated meat", "cell based meat", and "in vitro meat",[1] along with their corresponding hashtags "#labgrownmeat", "#culturedmeat", "#cultivatedmeat", "#cellbasedmeat", and "#invitromeat".[2] Alongside the three labels

[1] Although our search strings lacked hyphens, they were capable of capturing tweets that did contain them. We have hyphenated them in the text below wherever grammatically appropriate.

[2] These hashtags were included to capture more tweets relevant to our focal labels. In our data-cleaning and analysis processes, however, we did not distinguish between a given label-as-phrase and its corresponding hashtag. For more information, please refer to footnotes 4 and 5.

studied by Pilařová et al. (2022),[3] we included "in-vitro meat" and "lab-grown meat" due to their common usage, especially by cultured-meat industry leaders and early academic researchers on this topic (Goodwin and Shoulders, 2013; Malerich and Bryant, 2022). This selection was carefully considered, as choosing keywords for social media research can be challenging. In particular, an overly broad selection would have risked irrelevant data being collected due to varied interpretations: e.g., the phrase "clean meat" might have been tweeted in the irrelevant context of cleaning traditionally produced meat, while "synthetic meat" could have encompassed numerous plant- and fungi-based products.

Given our study's focus on the usage and discussion of the five above-mentioned labels,[4] we removed tweets from our analysis if they 1) contained more than one cultured-meat label[5] (n = 9,928) or 2) lacked any of our labels.[6] This left 360,988 tweets for label-frequency analysis. Next, we divided the dataset into two parts: non-retweets (n = 196,490), to be used for word-cloud visualization, and retweets (n = 164,498), to be used for social-network analysis. This approach avoided potential distortions of our word clouds by retweets' echo effects (Boon-Itt and Skunkan, 2020; Huangfu et al., 2022).

For word-cloud analysis, all mentions (i.e., @[username]), hashtag symbols ("#"), URLs, special symbols (e.g., "&amp"), and non-alphabetic characters were removed. All letters were then transformed into lowercase. Next, we removed all words that were included in the Python Natural Language Toolkit stop-word list (see https://www.nltk.org/), and/or that were less than three characters long. Additionally, we removed "meat", "lab", "grown", "cultured", "vitro", "cell", "based", "cultivated", "cultivatedmeat", "culturedmeat", "cellbasedmeat", "labgrownmeat", and "invitromeat", as these label-related words were considered to be relatively uninformative when analyzing the dicussions surrounding each label. Lastly, we performed lemmatization, i.e., removed inflectional endings to return words to their basic form.

We elected not to pre-process the retweet dataset, as our aim was to analyze the flow of information, not its content. Fig. 1 summarizes our workflow.

2.2. Longitudinal change in the volume of each label

To discern patterns of label usage on Twitter/X, we categorized each of the 360,988 tweets and retweets into one of five groups, based on which label it contained. We then calculated the monthly tweet counts for each label across the data-collection window.

2.3. Word clouds

We first generated one word cloud for each label to visualize the terms that occurred most frequently in discussions related to that label. We then created annual word clouds for each label to assess how public discourse around it changed and developed year by year. Each of these word clouds contains up to 60 terms. Following Shahid's (2017) approach, we analyzed these word clouds to identify the key topics of the discussions the tweets were embedded in.

2.4. Social-network analysis

2.4.1. The whole network

Social-network analysis involves using graph theory to examine and quantify connections and relationships among individuals, groups, organizations, and information sources (Eskandari et al., 2022). We deemed two users to have a connection if one retweeted at least one post by the other.

We began by generating a graph encompassing all retweets in our dataset, as an overview of the network of cultured meat-related conversations. Then, following Milani et al. (2020), we identified our 10 main influencers as the top 10 users in that whole network – as measured by betweenness centrality – who also had an in-degree centrality higher than 20. Betweenness centrality comprises the shortest paths between pairs of nodes that pass through a given node in a network; thus, a node with a high betweenness-centrality value serves as a bridge in its network, facilitating interaction by linking diverse communities together (Britt et al., 2020). In-degree centrality, on the other hand, is defined as the frequency of a user's posts being retweeted, and reflects their visibility within the network (Milani et al., 2020). Influencers who score highly on both these metrics are therefore likely to engage with multiple audiences and conversations (as indicated by high betweenness centrality) and to maintain significant visibility within their own networks (as indicated by high in-degree centrality).

2.4.2. Union of the ego networks of the identified influencers

To better understand the label-usage patterns of those groups of 10 influencers, following Tucci and Carneiro (2022), we visualized a union of their respective ego networks. An ego network comprises a focal individual, known as the ego, and all their direct contacts, known as alters. Such networks are fundamental to many studies of micro-level network structures, as they can reveal how a single user is connected to a network (Verweij, 2012). For our purposes, alters comprised both the set of users that retweeted an ego's tweets and the set that were retweeted by it. On that basis, we merged the 1.5-degree ego networks of the influencers, each including not only the alters' connections with the ego, but also their connections with one another (Eleta and Golbeck, 2012), to form a union network (Leone Sciabolazza et al., 2017).

2.4.3. Year-by-year network analysis

Following Yang and Sun (2021), we next conducted network analysis separately for each of the 13 calendar years covered by our data, applying five different colors to the edges to represent our five labels. For each of these single-year networks, we also quantitatively analyzed key properties including diameters, numbers of nodes and edges, average path lengths, average weighted degrees, and modularities (see Table 1).

3. Results

3.1. Longitudinal change in the volume of each label

As shown in Fig. 2 below and in Fig. 1 of the Supplementary Materials, "lab-grown meat" was the label most frequently encountered in the dataset used to conduct volume analysis (n = 360,988), accounting for 216,130 tweets (59.9%). It was followed by "cultured meat" with 77,957 tweets (21.6%) and "cultivated meat" with 37,620 tweets (10.4%). The labels "cell-based meat" and "in-vitro meat" accounted for 15,932 tweets (4.4%) and 13,349 tweets (3.7%), respectively.

[3] We did not use "cellbased meat", which Pilařová et al. (2022) used as a keyword to capture tweets related to the label "cell-based meat". As a main goal of the present study is to compare public usage of labels, to ensure consistency and a fair point of comparison, we used two keywords (i.e., the label-as-phrase itself and its corresponding hashtag) for each label

[4] Below, when applied to the present research's analysis and findings, "in-vitro meat", "cell-based meat", "cultivated meat", "cultured meat", and "lab-grown meat" refer to the label as a whole, i.e., encompass both those specific phrases and their corresponding hashtags.

[5] A tweet containing both a label-as-phrase and its corresponding hashtag, or where that phrase or hashtag appears once or multiple times, was considered to contain just one cultured-meat label. However, if a tweet contained two or more different labels – whether as phrases, hashtags, or both – we deemed it to contain more than one cultured-meat label and therefore excluded it.

[6] We observed 53,466 of the tweets we collected did not contain any of the keywords we used for data extraction. This discrepancy is presumably attributable to the data-collection mechanism utilized by Brandwatch. For example, some of these tweets could have been replies to or comments on original tweets that did contain our keywords.

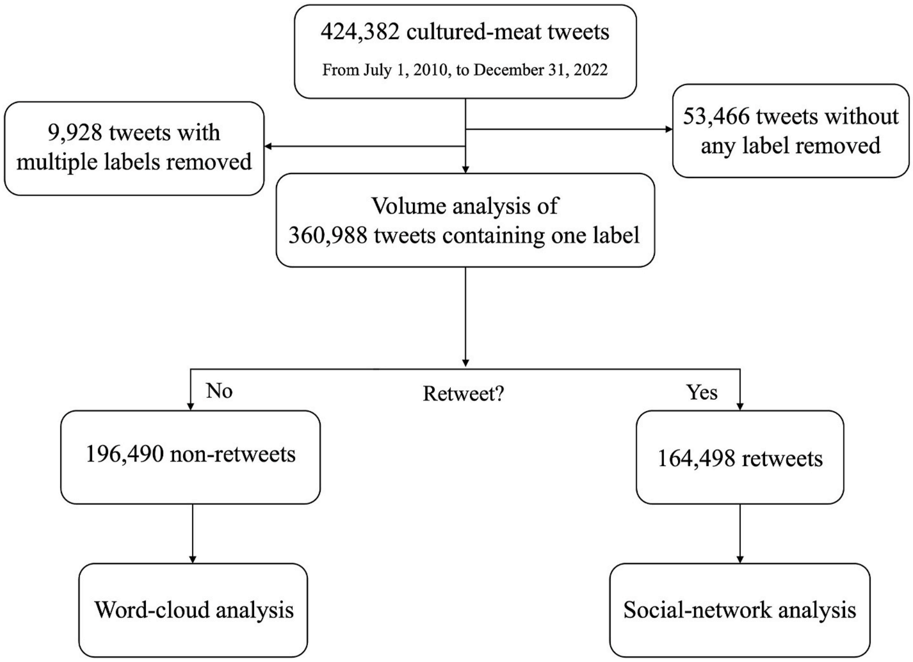

Fig. 1. Workflow of this study.

Table 1
Network metrics.

Metric	Definition
In-degree centrality	The number of directional links to a user from other users. In this study, it represents the number of times that user's tweets were retweeted
Out-degree centrality	The number of directional links from a user to other users. In this study, it represents the number of times that user retweeted others' tweets
Betweenness	The number of shortest paths that pass through a specific node. It indicates how central a node is to connecting any other pair of nodes, and thus how important it is in controlling the routes of information flow in the network
Average path length	The shortest average distance between two nodes, representing how easy or difficult it is to spread information through the whole network, with higher values indicating greater difficulty
Average weighted degree	The average sum of weights of the edges of nodes in a network. In our study, it refers to the general frequencies of retweeting by users in the network
Network diameter	The linear size of the retweet network. A smaller network diameter indicates that users in the network are more closely connected to each other
Modularity	A measurement of the quality of clustering. Higher modularity suggests that the network is more clusterized (i.e., there are more connections within each cluster but fewer connections between its clusters). When the clusters in a network are highly disconnected, the interactions among groups tend to be limited, which in turn reduces their access to new information

Note. Sources: Crescio et al. (2021); Lim et al. (2016); Sulis and De Lellis (2018).

Between mid-2010 and the end of 2015, however, “in-vitro meat” (22.4%) was second only to “lab-grown meat” (63.6%) as the most-seen label. And, starting in the second half of 2018, the frequency of “cell-based meat” noticeably increased, in keeping with the September 2018 decision by a group of cultured-meat startups to adopt this label and discontinue their use of “clean meat” (FoodNavigator, 2018). However, the usage frequency of “cell-based meat” has consistently remained at a relatively modest level.

Starting in 2019, the label “cultivated meat” gradually gained traction. This may be attributable to research findings by Szejda (2018), a research scientist at the Good Food Institute (GFI), that this label was more appealing to consumers than certain others including “cultured meat” and “cell-based meat”. Moreover, unlike “cell-based meat”, “cultivated meat” has exhibited an overall upward trend in usage. It may be important, in this context, that “cell-based meat” was the only one of our five labels that was not yet present in the 2010 data. At that point, the usage frequencies of “cultivated meat” and “cultured meat” were relatively low, but a notable surge in the latter occurred in August 2013, coinciding with the cooking of the first cultured beef burger (BBC News, 2013). “Lab-grown meat” was the most prevalent label in the vast majority of months within our data-collection period, whereas all four of the others experienced dramatic ups and downs.

We identified four events as corresponding to major spikes in the discussion of cultured meat on Twitter/X. The first (hereafter, “Event 1”), in August 2013, was the unveiling of the world's first cultured meat at a news conference in London (Post, 2014). Event 2, in December 2020, was Singapore's approval of a cultured-meat product for sale (Reuters, 2020). Event 3, in July 2022, was the release of a video of a burning factory, which the uploader claimed was a synthetic-meat facility that had been invested in by Bill Gates – a claim that was later debunked (Tulp, 2022). Event 4, which caused the final and largest spike, was a November 2022 statement by the FDA that it had “no further questions” regarding the production of cell-cultured chicken by Upside Foods (FDA, 2022). In Twitter/X discourse around these four events, “lab-grown meat” consistently emerged as the most frequently used label. However, the second most common labels varied, indicating evolving usage patterns.

3.2. Word clouds

3.2.1. Whole-dataset word clouds

We identified frequent terms and corresponding topics based on our interpretation of word-cloud figures, including those shown in Fig. 3. We found that the content discussed by Twitter/X users over the whole data-collection window varied depending on which label they were using. Common phrases in discussions around “in-vitro meat” included “petri dish”, “coming”, “soon”, “dinner”, and “plate”. All were probably linked to a Reuters article titled “Petri dish to dinner plate, in-vitro meat coming soon” (Kelland, 2011). Conversations about “in-vitro meat” not

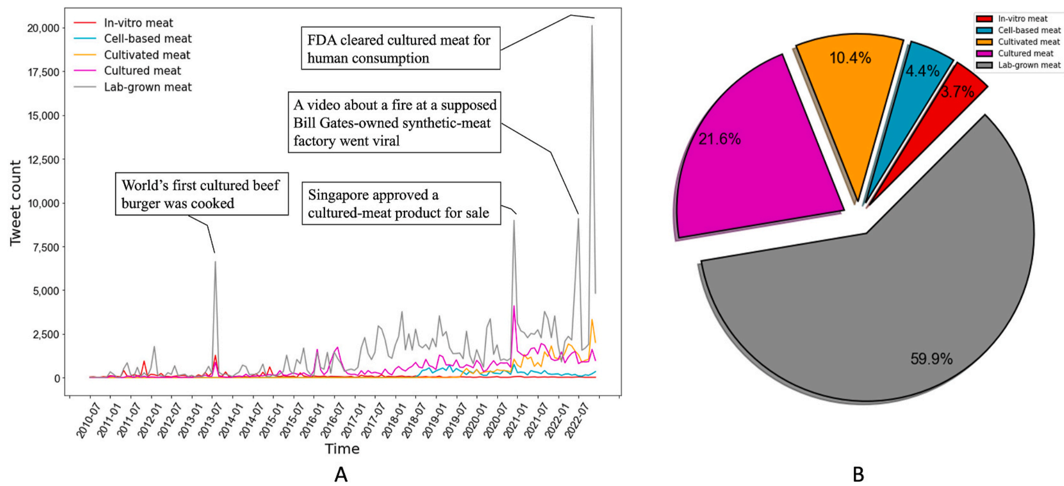

Fig. 2. (A) The number of tweets of each label, represented by different colors; (B) the proportion of the tweets containing each label. Events corresponding to the four most prominent peaks are highlighted. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

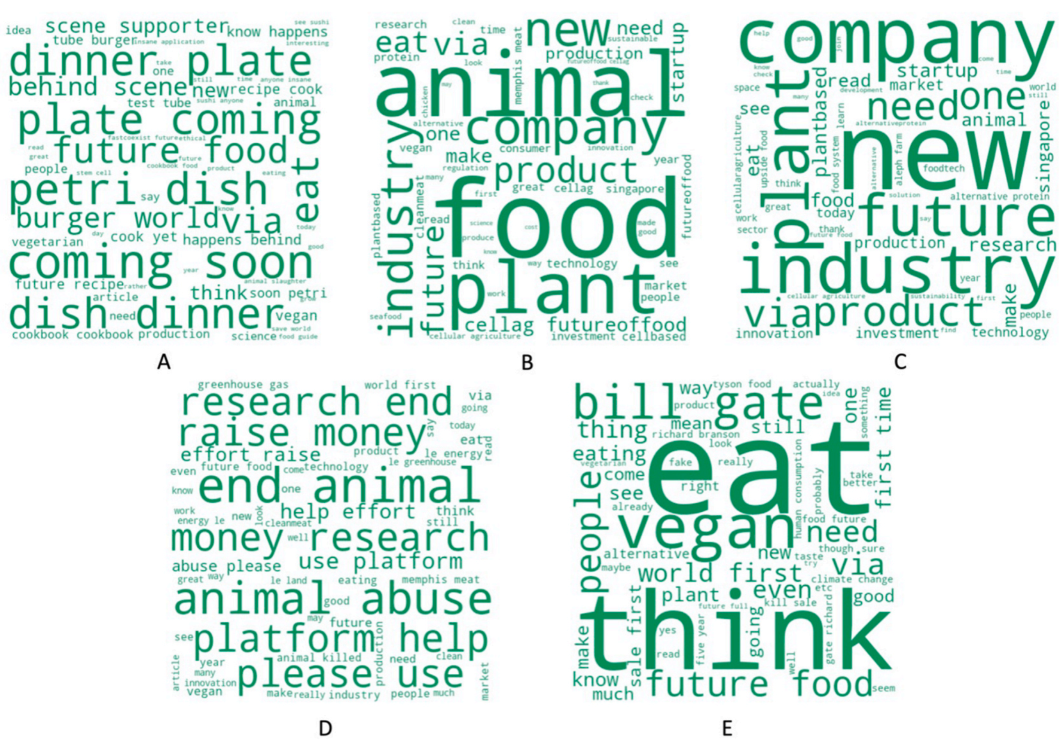

Fig. 3. The whole-dataset word clouds for (A) "in-vitro meat", (B) "cell-based meat", (C) "cultivated meat", (D) "cultured meat", and (E) "lab-grown meat".

linked to that article were sparse.

In tweets containing the "cell-based meat" label, the words "animal", "food", "plant", and "company" appeared frequently. "Animal" was likely to have referenced animal welfare-related ideas such as animal-free food and the avoidance of animal suffering, while "plant" probably reflected concepts related to plant-based meat. These words possibly indicate that the discourse around "cell-based meat" not only centered on its ethical attributes, but also positioned it in relation to meat alternatives, within a broader conversation about sustainable and ethical food choices.

Among tweets mentioning "cultivated meat", the terms "industry", "company", "new", and "future" were frequently invoked. This likely indicates that conversation's emphasis on business and product-development perspectives.

Tweets about "cultured meat", in contrast, frequently featured the terms "end", "animal", "abuse", "research", and "money". This likely indicates a diverse array of public concerns encompassing animal welfare, the scientific research underpinning cultured meat, and economic factors in and/or consequences of such meat's emergence.

Lastly, tweets related to "lab-grown meat" frequently incorporated the terms "eat", "think", "vegan", and "bill gate". Bill Gates and some other famous figures including Richard Branson are known to have invested in several cultured-meat companies. Based on our word-cloud results, discussions among Twitter/X users about the "lab-grown meat" label seem likely to have revolved around these famous personalities, as well as the potential impact of cultured meat on vegans and vegetarians.

3.2.2. Longitudinal changes in Twitter/X conversations around each label

The year-specific word clouds shown in our Supplementary

Material's Figs. 3–7 offer a dynamic view of the prevalent terms associated with each label over time. For example, in both the early years (specifically, 2010 and 2012) and more recent ones (specifically, 2018-22), the word "animal" was prominently featured in the "in-vitro meat" word clouds, likely suggesting conversations that revolved around animal welfare and cultured meat's potential ethical advantages.

As noted above, mentions of "cell-based meat" were relatively rare prior to 2019. Consequently, its word clouds for 2010-18 were highly susceptible to influence by individual tweets mentioning it, and might not accurately represent broader discussions. Indeed, the absence of relevant tweets resulted in empty word clouds for some years. Word clouds from specific years may reflect particular events. For instance, the 2018 word cloud for "cell-based meat" included regulation-related terms, likely because in that year, the USDA and FDA issued a joint statement on the regulation of "cell-cultured food products derived from livestock and poultry". Specifically, it was announced that the FDA oversaw "cell collection, cell banks, and cell growth and differentiation", while the USDA covered "the production and labeling of food products derived from" such cells (USDA, 2018). Additionally, in post-2019 word clouds for "cell-based meat", the prominence of the terms "animal", "food", and "plant" might suggest that Twitter/X discourse was primarily centered around the ethical/animal-welfare impacts of this novel product category, along with comparisons to plant-based meat.

Similarly, the yearly tweet volume for the "cultivated meat" label remained below 50 until 2019. Therefore, it would be imprudent to draw firm conclusions from its early word clouds. From 2019 onwards, "industry", "company", "plant", and "product" were consistently among the most prominent terms, possibly indicating broader discussions encompassing business and product development.

The prominence of the words "taste" and "test" in the 2013 word cloud for "cultured meat" likely reflects Event 1: the public tasting of the world's first cultured beef burger, which occurred that year. Similarly, the emergence of the term "tyson food" in the "cultured meat" word cloud for 2018 may hint at Tyson Foods' (2018) announcement of an investment in a cultured-meat company, Memphis Meats.

The 2013 word cloud for "lab-grown meat" was also possibly related to Event 1, insofar as an article starting with the sentence "On Monday, three lucky diners nibbled a $325,000 burger" went viral on Twitter/X that year (Datar, 2013). The above-mentioned naming of prominent investors Bill Gates and Richard Branson first emerged in the "lab-grown meat" word cloud for 2017 and recurred in 2018. However, while "bill gate" continued to appear in the word clouds for 2020-22, "richard branson" did not appear in those subsquent word clouds. And in the same label's 2022 word cloud, the terms "fda", "approval", "human", and "consumption" appeared prominently, probably due to Event 4.

3.3. Social-network analysis

3.3.1. Overall network graph

Our analysis identified a comprehensive retweet network comprising 119,947 unique users. Each such user either retweeted or was retweeted at least once during discussions related to cultured meat over the 12.5-year period covered by our data. Fig. 4A visualizes this overall retweet network, and includes 1) distinct groups of users who interacted with one another frequently, termed communities or clusters; and 2) less-engaged users at the periphery of the network. Edges of different colors depict label-adoption patterns. Specifically, on the left-hand side of this graph, a group of users is connected primarily by gray edges. This indicates that when cultured meat-related information was disseminated among these users, "lab-grown meat" was the label they used almost exclusively to refer to this product. On the right-hand side, edges are predominantly orange, magenta, and blue, representing the labels "cultivated meat", "cultured meat", and "cell-based meat", respectively. This indicates how information related to cultured meat using these three labels was disseminated among these users, including the influencers we identified. Patterns of information dissemination related to these influencers will be discussed in the section on ego networks, below.

The sizes of the nodes in Fig. 4A depict their betweenness-centrality values, with larger sizes representing higher values, i.e., those nodes' greater importance in facilitating the retweet network's information flow. Table 2 ranks the influencers by their betweenness centrality and provides descriptions and in-degree centrality values for each of them. The node with the highest betweenness is @NewHarvestOrg, a nonprofit supporting cultured-meat research (New Harvest, 2024). The second-, third-, and fourth-largest nodes are all associated with GFI, a nonprofit organization advocating the development of plant-based meat, dairy, and egg products as well as cultured meat (GFI, 2021a). Specifically, @elliotswartz represents the lead scientist from GFI, @GoodFoodInst is its official Twitter/X account, and @BruceGFriedrich represents its founder. Among the remaining six influencers we identified, four – specifically @cellagritech,[7] @WIRED, @Protein_Report, and @mattsreynolds1 – are news-media outlets or affiliated with such outlets. One represented a prominent cultured-meat company, @MemphisMeats, which is currently operating under the name Upside Foods. The final influencer is an independent writer denoted as @benwurgaft. These influencers' in-degree centrality values are all greater than 100, indicating that all had sizable audience bases and that their posts were frequently retweeted.

3.3.2. Union-network graph

Fig. 4B shows the union network made up of the ego networks of the influencers we identified, comprising 4,804 unique users (4.0% of the overall network), and 12,553 retweet connections (8.7% of the overall network). By focusing exclusively on the influencers and their direct contacts during this phase of our analysis, we were able to ascertain these key users' respective and collective influences on information dissemination, as well as their patterns of label adoption. The size of the union-network graph reflects how many alters, within the category of Twitter/X users, these influencers interacted with. The colors of the edges in the union-network graph indicate these influencers' label-usage patterns, with the main ones being magenta ("cultured meat"), orange ("cultivated meat"), and blue ("cell-based meat"). The relatively high frequency of the label "lab-grown meat" on Twitter/X, as illustrated in Fig. 2, contrasts with its limited use by these influencers. This appears to suggest that they took a different view of this label than most Twitter/X users did. For instance, @NewHarvestOrg predominantly links to magenta edges, emphasizing heavy use of the label "cultured meat", though other labels like "cultivated meat" (orange edges), "in-vitro meat" (red edges) and "cell-based meat" (blue edges) are also represented. Conversely, for GFI-associated users like @elliotswartz, @GoodFoodInst, and @BruceGFriedrich, the prevailing edge color is orange, while users such as @MemphisMeats, @Cellagritech, and @Protein_Report mainly connect through blue edges. Meanwhile, @WIRED's links, primarily in magenta, gray, and orange, suggest varied label usage; and @mattsretnolds1's connections are mostly orange and blue, reflecting a dual focus on "cultivated meat" and "cell-based meat".

3.3.3. Dynamic network analysis

Fig. 5, showing each year's network graph, allows us to chronologically trace the evolution of both the network's structure and of labeling patterns as represented by edge colors. The 2010 network, with only 90 nodes, shows no clear community and was dominated by red edges ("in-vitro meat") and gray ones ("lab-grown meat"). However, Twitter/X users started forming larger and more connected clusters in 2011-14, when the predominant edge colors were gray, magenta, and red, corresponding to the labels "lab-grown meat", "cultured meat", and "in-

[7] The Twitter/X account @cellagritech, which represents the news-media outlet CellAgri, should not be confused with Cell Agritech, a company directly involved in cultured-meat production.

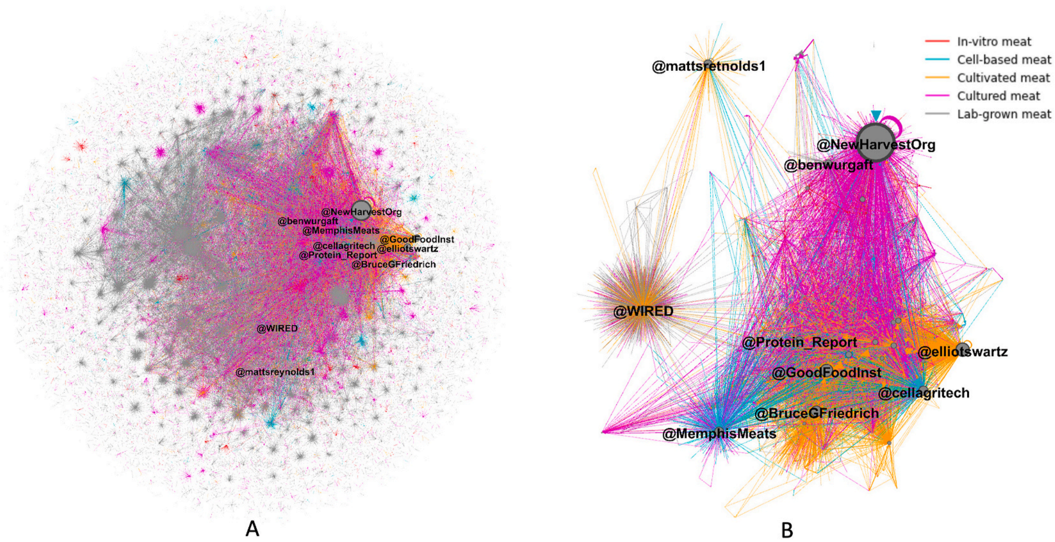

Fig. 4. (A) The entire retweet network; (B) the union network made up of the 1.5-degree ego networks of the identified influencers, with node sizes proportional to betweenness centrality. Key influencers, identified by their values of betweenness centrality and in-degree centrality, are labeled. The color of each edge represents the label used in the corresponding tweet. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Influencers ranked by their betweenness-centrality scores.

Rank by betweenness centrality	Account name[a]	Account type	In-degree centrality[b]
1	*@NewHarvestOrg*	Non-profit: New Harvest	532
2	*@elliotswartz*	Non-profit: GFI scientist	644
3	*@GoodFoodInst*	Non-profit: GFI	825
4	*@BruceGFriedrich*	Non-profit: GFI founder	629
5	*@cellagritech*	News media	309
6	*@MemphisMeats*[c]	Cultured-meat company	642
7	*@mattsreynolds1*	News media (WIRED writer)	101
8	*@Protein_Report*	News media	103
9	*@WIRED*	News media	1,555
10	*@benwurgaft*	Individual writer	150

Note. GFI = the Good Food Institute.
[a] account names are those in use when the data were posted.
[b] a measure of the frequency of the user's tweets being retweeted.
[c] Now known as @upsidefoods.

vitro meat", respectively. In 2015, a node at the core of the network is connected with multiple surrounding nodes. Such a pattern suggests that the central node – i.e., @NewHarvestOrg, in this case – likely played a crucial role in the distribution and amplification of content or ideas, i.e., was a key influencer. The network graphs for 2016-18 display a similar pattern: at the core of the network, a group of users primarily used the label "cultured meat", while in its periphery, numerous distinct small clusters reflect extensive use of "lab-grown meat". In the same period, the users with high in-degree centrality who frequently linked to magenta/"cultured meat" edges primarily included @MemphisMeats, @vegan, and @NewHarvestOrg. In the 2019 graph, blue/"cell-based meat" edges appear more prominently, but remain limited to a few groups located near the core of the network, including @TEDTalks, @MemphisMeats, and @ezralkein (a columnist from the *New York Times*). While the label "cultivated meat" was proposed by GFI in 2019, orange edges corresponding to it were more noticeable in the following year's graph. In 2021, there was a decrease in orange/"cultivated meat" edges and an increase in magenta/"cultured meat" ones. Lastly, the 2022 network can be divided into two main clusters. In its upper region, users can be seen adopting a diverse array of labels, notably including orange/"cultivated meat", magenta/"cultured meat", and blue/"cell-based meat". In its lower region, on the other hand, their adoption of the label "lab-grown meat" is universal; and interaction between these two clusters is low.

As detailed in the Supplementary Material's Fig. 8, we observed a consistent annual increase in both nodes and edges from 2010 to 2022, with the exception of a noticeable decline from 2013 to 2014. Growth in the numbers of nodes and edges typically indicates increases in the number of participants in the focal discourse and the number of interactions in it. A notable increase in the number of nodes and edges from 2012 to 2013 and the above-mentioned decrease might both have been associated with the intense discussions surrounding Event 1. This pattern of rapid, intense activity followed by periods of inactivity has often been observed in social networks (e.g., Kalyanam et al., 2016).

Concurrently, our focal network's scope markedly expanded, with its diameter growing from 2 to 16 from 2010 to 2022. That is, over this period, it connected a broader spectrum of users, reflecting a wider spread of information across Twitter/X communities. This expansion coincided with an increase in average path length, indicating more complex information dissemination, which could reasonably be anticipated to take longer to propagate within the network. Additionally, an upward trend in average weighted degree appears to indicate heightened retweeting activity. While there was a general downward trend in modularity starting in 2011, values remained high, i.e., above 0.8 in that and all subsequent years. High modularity reflects a network in which there are clear divisions or communities, indicating that information or messages might circulate intensively within such subgroups, but less so between them.

4. Discussion

4.1. Label frequency

The patterns observed in our volume analysis highlight the evolving nature of how Twitter/X users adopted five different labels for cultured meat. Importantly, the example of "in-vitro meat", whose frequency dropped from 2,891 in 2013 to 280 in 2022, suggests that initial wide adoption of a particular label on Twitter/X does not guarantee its sustained usage over time. Conversely, new labels can undergo dramatic increases in their frequency of use on the platform, such as "cell-based

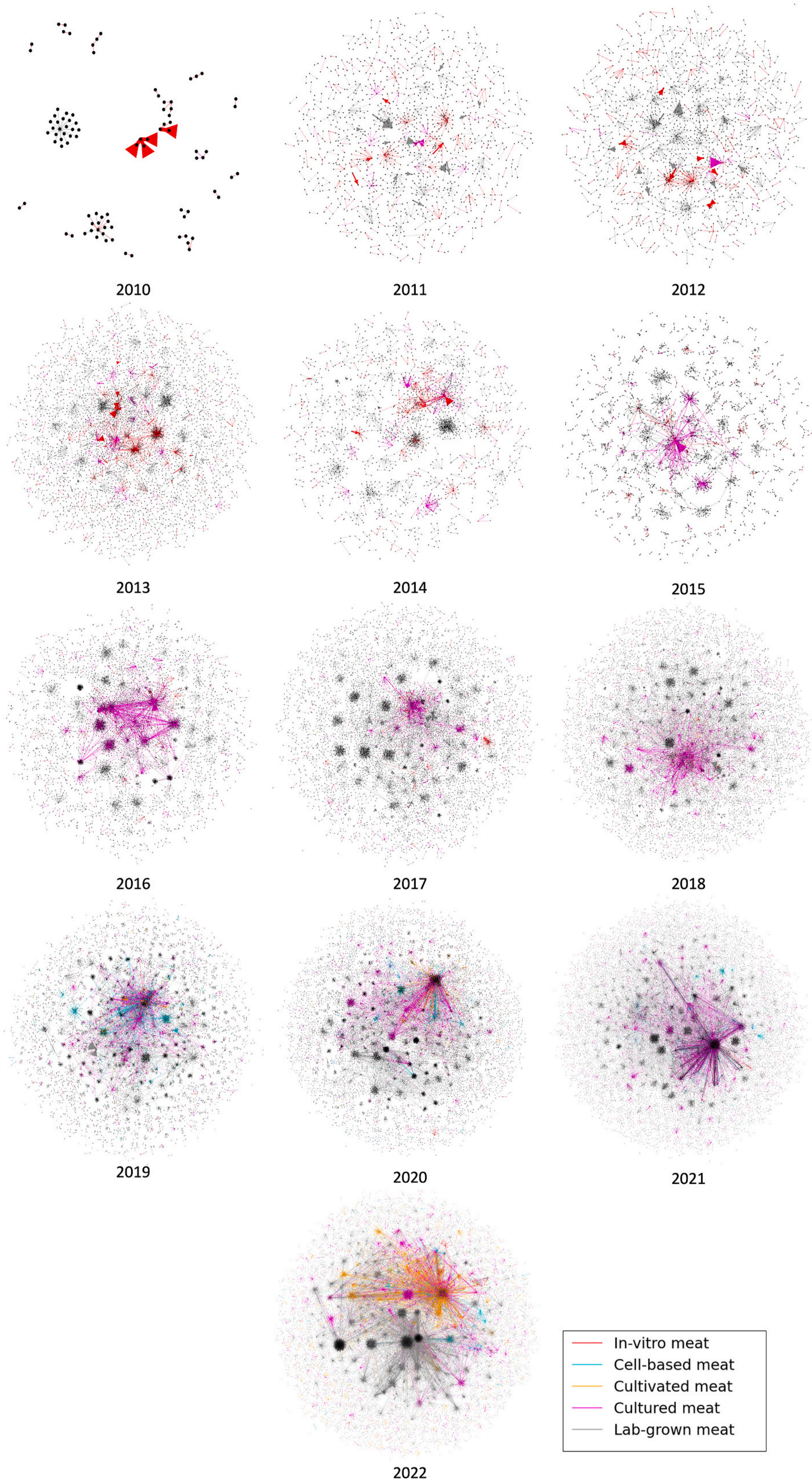

Fig. 5. Retweet network graphs of each year's data. Edge colors indicate which label was contained in that tweet. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

meat", which grew from three mentions in 2017 to 1,886 in 2018 and 4,864 in 2019; and "cultivated meat", which rose from 40 mentions in 2018 to 1,466 in 2019 and 5,069 in 2020. That is, far from being static, label choice among Twitter/X users is potentially influenced by external advocacy and shifting public perceptions. The changing label preferences of the GFI and various cultured-meat startups appear to exemplify this phenomenon. "Clean meat", which was initially endorsed by the GFI in 2016 (Friedrich, 2016), was reconsidered in 2018. During the Good Food Conference hosted by the GFI that year, startups collectively decided to move away from this label due to its potential implication that conventional meat is "unclean", and opted instead for "cell-based meat" (FoodNavigator, 2018). However, this latter label was soon replaced when, in 2019, the GFI suggested that "cultivated meat" was a more fitting label (GFI, 2019). The future landscape of labeling in this field likewise remains dynamic, with no barriers to the emergence of new labels that will also necessitate careful consideration by stakeholders. As the field of cultured meat continues to evolve, finding a universally accepted label remains a challenge.

4.2. Word clouds

Our word-cloud analyses shed light on the nuances of dialogues and public narratives around various cultured-meat labels, revealing shifts in their foci and in the prominence of their other key terms. Crucially, the content/themes of these dialogues and narratives varied sharply across the five labels. Several factors could account for these disparities. First, the compositions of the Twitter/X-user groups that were prone to using each label differed. While there were undoubtedly some overlaps, each label typically corresponded to a distinct user base. For example, "lab-grown meat" was a label often adopted by the media (Bryant and Barnett, 2019), whereas "cultivated meat" was favored by cultured-meat companies (GFI, 2021b). Thus, the different content/foci mentioned above probably reflected the diverse interests and priorities of these varied user groups.

Second, as the results of our volume analysis indicate, the various labels waxed and waned in popularity over the studied period. For instance, mentions of "in-vitro meat" were primarily concentrated in the earlier years, whereas "cell-based meat" and "cultivated meat" only gained traction beginning in 2018 and 2019, respectively. Over time, as public awareness and understanding of cultured meat expanded, discussions of it would naturally have evolved. In the latter years of the studied period, several common themes related to animal welfare, plant-based meat, and the commercialization of cultured meat became more prominent in this discourse, signaled by an increased prevalence of terms like "animal", "vegan", "plant", and "company". As global demand for meat remains robust and is growing consistently (Jia et al., 2023), alternative edible proteins obtained from sources including vegetables, grains, microorganisms, and insects have attracted considerable attention due to their reduced environmental impact (Grossmann and Weiss, 2021). Unlike other alternative-protein sources, however, cultured meat is anticipated to offer flavor profiles comparable or even identical to those of conventional meat (Chen et al., 2022). Conceivably, stakeholders have begun directly comparing cultured meat to plant-based meat as a strategy for showcasing what they perceive as the former's unique benefits. Moreover, discussions of cultured meat's benefits could extend beyond sensory experience. From an ethical perspective, cultured meat is designed to substantially reduce the number of animals required, relative to traditional farming, which some scholars suggest might enhance its appeal to some vegans and vegetarians (Chriki and Hocquette, 2020).

A third potentially important driver of the differences between the discussions surrounding these five labels might be the public's interpretation of them, which may also affect their popularity. As previous studies have demonstrated, certain labels can evoke distinct associations. For example, "cultured meat" has been found to evoke science-related associations (Bryant and Barnett, 2019), whereas "lab-grown meat" tends to be associated with human interference with nature (Watson, 2020). This is consistent with our findings that science-related words such as "research" and "technology" frequently showed up in "cultured meat"-related Twitter/X conversations. Our volume analysis, meanwhile, reveals that Twitter/X users infrequently utilized the label "in-vitro meat", and our word-cloud results further suggest that discussions related to that label were probably linked to an article by Kelland (2011). That article covered the early work of Mark Post, a scientist at Maastricht University in the Netherlands, whose research eventually led to the development of the world's first lab-grown hamburger, unveiled in 2013. It also highlighted this innovation's potentially large environmental benefits, along with various challenges to making it appealing, including taste and cost. Szejda (2018) found that "in-vitro meat" was less appealing than many other labels, including all four of the others we examined; and this, too, could help account both for its lower usage frequency and the limited variety of topics in the surrounding discussions. In the sampled Twitter/X conversations about "cell-based meat", on the other hand, the emphases on animal welfare and this product's distinction from and/or relation to plant-based meat were likely due to the label's descriptive nature, which arguably elucidates the product's true essence (e.g., Szejda, 2018). This specificity could have encouraged Twitter/X users to distinguish "cell-based meat" from traditional meat, fostering deeper discussions about the unique qualities of cultured meat.

These findings offer valuable insights for stakeholders, especially brands, marketers, and regulators. For cultured-meat companies, understanding the unique attributes and public perceptions associated with each label can guide the creation of communication strategies tailored to different consumer segments, and thus to optimal product positioning. However, their labeling choices could become complex balancing acts. They would have to ensure that the chosen label clearly and completely identifies the product, as mandated by regulatory bodies (e.g., USDA, 2023), while also considering its potential impact on consumers' mental associations, attitudes, and behavioral intentions (Bryant and Barnett, 2019). For regulatory entities, Twitter/X discourse can potentially provide a deeper understanding of public attitudes and concerns, facilitating the formulation of more appropriate policies and guidance.

4.3. Network analysis

One study identified 19 cultured-meat companies that posted a total of 7,942 tweets between 2016 and early 2021 (Su et al., 2023). However, while these companies were active in producing content during our data-collection window, they did not appear to play key roles in the wider dissemination of cultured meat-related information across Twitter/X. Indeed, among the key influencers in the retweet networks identified in the present study, only one was a cultured-meat company (i.e., @MemphisMeats, currently @upsidefoods).

The influencers identified in our study displayed varied approaches to label usage, with some using multiple labels and others being highly consistent in their terminology. For instance, New Harvest did not demonstrate a clear preference for any specific label, as illustrated in our Supplementary Material's Fig. 2B. In contrast, GFI primarily used "cell-based meat" between mid-2018 and mid-2019, and "cultivated meat" from that point onward, as shown in the Supplementary Material's Fig. 2A.

GFI advocated for "clean meat", "cell-based meat", and "cultivated meat" at various times (FoodNavigator, 2018; Friedrich, 2016; GFI, 2019), and such advocacy might be associated with the noticeable increases in the frequencies of both "cell-based meat" and "cultivated meat" that we observed. However, our retweet-network analysis indicates that these two labels were tweeted or retweeted by a relatively low number of the relevant Twitter/X users. In contrast, two-thirds of them retweeted the label "lab-grown meat" and/or used it in tweets they composed themselves. This divergence points to a potentially large gap between institutional advocacy of a given label and wider public adoption of it. Ong et al. (2020) argued that use of the "lab-grown meat" label could "differentiate products" and was "not derogatory to conventional meat" (p. 226). If this is the case, then the adoption of "lab-grown meat" by a dominant subgroup of our cultured-meat retweet network might stem from its members' desire for clarity and/or neutrality in how cultured meat is presented and understood in public discourse, despite this label's possible evocations of unnaturalness (Bryant and Barnett, 2019) and relative lack of consumer appeal (Szejda, 2018).

The high modularity we observed in the retweet network was a further indication of its pronounced clustering. In other words, while the members of some readily discernible user groups/communities were tightly interlinked with one another, their respective groups/communities operated somewhat in isolation from others. This phenomenon has important practical implications, particularly for whole-network information flow. For instance, if User A and User B are both prominent and frequently retweeted within their respective communities, high modularity in a retweet network suggests that there is minimal overlap between the Twitter/X followers of A and those of B, as noted by Chu et al. (2015). Consequently, information disseminated by User A may not readily flow into User B's community, and vice versa. This phenomenon can be likened to the "echo chamber" effect on social media, whereby information circulates within closed communities (Cinelli et al., 2020). Within these "chambers", consistent exposure to specific terminologies would logically tend to reinforce labeling habits, thereby making both the wide adoption of a new cultured-meat label and the establishment of consistent nomenclature more challenging.

Crucially, cultured-meat labels are not mere terminological choices: each has unique connotations that could shape public understanding and opinion. Moreover, reinforcement of particular labels as "correct" within mutually isolated groups of social media users would tend to magnify these perceptions, potentially skewing public understanding and opinion. Therefore, efforts should be directed not only towards devising appropriate labels, but also towards bridging the communication divides between these groups. This would ensure a more even spread of information and mitigate the potential biases or misconceptions associated with specific labels.

5. Limitations and future directions

The current study has some limitations. First, we did not include all the cultured-meat labels that were current or that emerged during our data-collection window. For instance, because they might not be perceived as neutral by the conventional-meat industry (Ong et al., 2020), "clean meat" and "slaughter-free meat" were not selected, despite previous findings that they have higher consumer appeal than all the labels we included (Szejda, 2018). Moreover, new labels that satisfy the inclusion criteria might continue to emerge. In any case, each label in our study represented a separate dataset, and most of our analyses were automated and unsupervised. Consequently, it would be straightforward to utilize our versatile approach for analyses of any number of additional labels in the future.

Second, the demographic composition of Twitter/X users is not fully representative of wider populations (Jaidka et al., 2020). In the United States, for example, more than 55% of Twitter/X users are between 18 and 34 years old (Statista, 2021), and previous research has reported that younger consumers are more likely to express favorable views of cultured meat (Bryant and Barnett, 2020). So, leaving to one side the potential for today's Twitter/X discourse to shape tomorrow's reality, our data should be interpreted with great caution as an index of opinions on cultured meat held by the public at large.

6. Conclusions

This study investigated the usage patterns, discussion topics, and dissemination patterns associated with five cultured-meat labels by analyzing a large-scale Twitter/X dataset. Throughout the period we studied, our five focal labels for cultured meat not only exhibited varied usage patterns, but also were associated with differing shifts in public opinions and perceptions. These patterns may imply a complex two-way interplay between the choice of a given label and public perceptions of what that label means.

Crucially, stakeholders including but not limited to companies at the forefront of cultured-meat innovation, media outlets, and regulatory bodies should seek to navigate the labeling process with caution and strategic foresight. This will involve understanding the potential repercussions of label choices and all stakeholders' diverse requirements and expectations around nomenclature. There is a need for a coordinated effort to create and promote a consistent nomenclature that can help unify communication across different sectors and communities. Future research could usefully investigate strategies to bridge communication gaps among stakeholder groups, as such bridging would tend to facilitate more effective information dissemination and a cohesive understanding of and consensus about cultured-meat products among them.

CRediT authorship contribution statement

Tianli Chen: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Leona Yi-Fan Su:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing. **Yee Man Margaret Ng:** Conceptualization, Methodology, Writing – review & editing. **Yi-Cheng Wang:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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