Systematic review of sensing technology for detecting food intake

YUZHI LIU, University of Twente, The Netherlands

Obesity has emerged as a critical global health challenge, primarily driven by chronic imbalances between energy intake and expenditure. Weight management strategies have become increasingly vital, with non-pharmacological interventions—including dietary modification and physical exercise—representing the predominant therapeutic approach. However, current dietary assessment methods rely heavily on self-reporting, which introduces substantial measurement errors and challenges in maintaining long-term adherence. While existing systematic reviews provide valuable insights, the most recent comprehensive analysis concludes at 2020, potentially overlooking significant technological and methodological advances in the field.

This systematic review examines literature from 2021 to identify emerging research dimensions and derive implications for future clinical practice and research directions. Following systematic screening of 316 articles, 34 studies met inclusion criteria for analysis.

Result found that the most focused dimension in 2021 is 'when', counted for 59 percent of all three dimensions, the other two dimension 'what' and 'how much' counted for 21 percent respectively. The most widely detected eating phase is 'oral processing',appeared 22 out of 34 times, counted for 65 percent of all the studies. The most used sensing principle is 'combination', appeared 14 out of 34 times, counted for 42 percent of all the articles. The 'Motion' + 'Vision' is the most widely used combination set, appeared 7 out of 14 times, counted for all the 'combination' sensing principle.

Comparative analysis with previous systematic reviews reveals consistent emphasis on 'when' dimension detection and eating phase 'oral processing' research, while identifying notable shifts in eating phase 'ingestion' research and sensor location 'face' deployment. These findings suggest continued prioritization of foundational detection capabilities while indicating emerging trends toward multimodal sensing. However, single-year analysis limitations may influence observed patterns, necessitating cautious interpretation of apparent research trends.

Additional Key Words and Phrases: Automatic detection

1 INTRODUCTION

Obesity is a global health crisis, with a total of 1.03 billion people who are diagnosed with obesity[28]. This condition fundamentally results from a chronic imbalance between energy intake and energy expenditure[7], where excess energy is stored as adipose tissue. Preventing obesity can significantly reduce the risk of various diseases, for example, all-cause mortality, type 2 diabetes, cardiovascular disease, and musculoskeletal burden[13].

Given the significant health burden of obesity, effective weight management strategies are crucial. Non-pharmacological interventions, which refer to the health care approaches that do not involve medication[17]. represent the most popular weight management approach. According to the study, 52 percent of individuals pursuing weight management utilize the following methods[17].

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Dietary monitoring forms the cornerstone of non-pharmacological weight management, with three primary assessment methods currently employed[43]: 24-hour dietary recall, food frequency questionnaires, and food diaries. Each method offers distinct advantages but also presents significant limitations.

The 24-hour dietary recall requires the users to retrospectively record their nutritional intake from the previous day[43]. While this approach is simple and cost-effective, research from Mendez[25] demonstrates that people tend to underestimate their energy intake, particularly among overweight individuals are more likely to underreport consumption of certain foods,especially like snacks[25].

Food frequency questionnaire involve users recording their consumption patterns of specific types over extended periods[47]. This method effectively captures long-term dietary habits but lacks precision in quantifying actual energy intake[47].

Food diaries require real-time documentation of all food consumption[4], When properly executed, this method provides the highest accuracy for tracking calories and nutritional content. However, this recording requirements often lead to poor adherence, with research showing significant participant dropout rates over time[46].

This raises a critical question: can we develop an integrated approach that harnesses the strengths of these three methodologies while mitigating their respective limitations?

Recent technological advances offer promising solutions to these dietary monitoring challenges. Haarman et al.[14] highlight the emergence of different technology tools that facilitate self-reporting without requiring users to possess specialized background knowledge or perform additional manual work during food consumption.

The research[14] introduces the concept of automated food intake detection, a technological approach that uses sensors to identify eating behaviors without manual input or self-reporting by users[14]. This represents a new field that is different from traditional methods which heavily rely on user compliance and memory.

Automated food intake detection systems address the three fundamental dimensions of dietary assessment that previously required manual reporting: timing of consumption (when), food identification (what), and portion quantification (how much)[14]. By using various sensor technologies, these systems can passively capture the continuous information.

The field employs diverse sensing principles for automatic food intake detection[5]. For example, accelerometer, camera and gyroscope, accelerometer and gyroscope could be categorised as motion sensing while camera would be categorised as vision sensing. There are also many sensor types would be discussed in the following paragraphs, each sensing modality offers unique advantages for different aspects of dietary monitoring.

Research by Sazanov[37] demonstrates that automatic sensor systems can effectively monitor eating events by detecting distinct eating phases, including chewing, swallowing, and biting. Each eating phase generates unique acoustic and movement signatures, making it crucial for automated food intake detection[37].

Haarman et al.[14] conducted a scoping review on automated food intake detection, examining literature from 2015 to 2020.

This scoping review[14] is highly informative for readers, but since 2020, significant technological progress has emerged in automated food intake detection. For instance, Jia et al.[19] demonstrated that artificial intelligence integration substantially improves assessment performance, while non-invasive automatic detection technologies have gained increasing prominence[37].

This study presents a systematic review of sensing technologies for food intake detection published in 2021, building upon the work of Haarman et al.[14]. From an initial search yielding 316 articles, inclusion and exclusion criteria were applied to identify relevant studies. The included articles were subsequently categorized and analyzed based on their primary focus dimensions, sensing principles, and targeted eating phases.I would like to see how many similarities and differences are there by compared to the work by Haarman et al. [14].

The analysis addresses the research question: **Which dimension was focused on the most in 2021,'when','what' or 'how much'?**

Along with the sub-research: **1. What sensing principle was most frequently employed in 2021? 2. What eating phases received the most research focus in 2021?**

2 MATERIALS AND METHODS

2.1 Literature search

The electronic database Scopus was used to search the articles, search table(Table 1) was provided by Professor Haarman et al.[14].

Under the category: (1)Type of food; (2) Timing of food intake; (3)Quantity of food. "OR" operator was used to connect these categories in between.

Under the category: (4)Sensing technology; and (5)Validation. "AND" operator was used to connect each other.

For category: (3)Quantity of food and (4)Sensing technology. "AND" operator was used to connect in between.

For category: (6)Language was to make sure that only language in English will be included in the systematic analysis.

For all the elements in the line of each category, "OR" operator was used to connect each other.

For example, ("Food choice" OR "Food composition") OR ("Bite" OR "Swallow") OR ("Portion size" OR "Portion weight") AND ("Sensor" OR "Wearable") AND ("Validat*" OR "Evaluat*") AND (LIMIT-TO (LANGUAGE , "English")).

2.2 Study selection

I did the same selection as Haarman et al.[14],but focused at the year 2021. For the **Inclusion criteria**: (1) Sensing technology is used to measure at least one of the three dimensions of food intake (when, what, how much); (2) Intended use of the technology was to measure dietary intake in a real-life setting; (3) The study includes a description of the technology's performance and validation process; (4) Only English article will be included. Publication year is 2021.

For the **Exclusion criteria**: (1) Studies involving infants or animals; (2) Technologies that rely solely on smartphone applications or smartphone-based self-reporting applications as sensing technologies; and (3) Technologies intended for diagnostic purposes (e.g., medical or clinical applications), food characteristic characterisation (e.g., food texture or oral processing properties), or food screening (e.g., for safety reasons). Article titles and abstracts serve as the basis for initial screening.

2.3 Data extraction

By extracting different categories, readers can gain a deeper understanding of various detecting dimensions, sensing principles and other categories that demonstrate the automatic testing process.

Year, Author, Title, and Reference Number: Citing information from the bibliography[14].

Sensing principle: (1)Motion, track the object based on the movement[14]. (2)Object labeling, capture the presence of an object[14]. (3)Spectral analysis, capture the wavelength of an object[**?**].(4)Conductance, capture the electrical potential of an object[14]. (5)Strain, capture the stress of an object[14]. (6)Vision, capture images of an object[14]. (7)Sound,capture the sound of an object[14]. (8)Combination. For (8)Combination, if there is more than one sensing principle mentioned above are used, then it is considered combination[14].

Sensor type: Identifying the type of sensor employed in the measurement set-up[14].

Number of sensors: Indicating how many of each particular kind of sensor were used in the measurement setup[14].

Sensing location:(1)Face[14]. (2)Ear,including the area around the ear[14].(3)Intra-oral[14]. (4)Neck[14]. (5)Torso[14]. (6)Extremities,including arms and wrists[14]. (7)External,the device that were not worn on-body of the user[14].

Location details: Refer to the original location that author mentioned in their paper[14].

Eating phase: (1)Preparation, which means food preparation prior to the start of the meal[14]. (2) ingestion, which means food retrieval, mouthpiece, and bite[14]. (3) oral processing, which means chewing sequence, liquid transport[14]. (4) swallowing, which means liquid and/or solid swallow[14]. (5) digestion which means gastric mobility, cardiac response, glucose com- position, body weight, and thermogenesis[14].(6) conclusion, which means cleaning, weighing the leftover food[14]. (7) Combination. For (7)Combination means those sensing cover more than one phase mentioned above[**?**].

Dimensions: (1) When[14]. (2) What[14]. (3) How much[14].

Sub-dimensions: (1) Intake gestures[14]. (2) Bites/sips[14]. (3) Chews[14]. (4) Swallow [14]. (5) Detection of eating/drinking events[14].

Measures of food intake: Under sub-dimension "chew", there is "chewing recognition"[14]. Under sub-dimension "Events", there are "Eating recognition", "Drinking recognition" and "Eating and drinking recognition"[14]. Under sub-dimension "Foods", there is "Product classification"[14]. Under sub-dimension "Mass", there is "Mass recognition"[14]. Under sub-dimension "Nutrients", there is "Nutrient intake recognition"[14].

Measurement details: Despite reporting on the same measure, several research may differ in how they analyzed the data[14]. For example, there is "Eating vs. other" under measure "Eating detection".

Type of food: Referring to the categories that were used in the research[14].

Table 1. Search table

Type of food	Timing of food intake	Quantity of food	Sensing technology	Validation	Language
"Food choice"	"Bite"	"Portion size"	"Sensor"	"Validat*"	English
"Food composition"	"Swallow*"	"Portion weight"	"Wearable"	"Evaluat*"	-
"Food type"	"Mastication"	"Meal size"	"Worn"	"Accuracy"	-
"Food intake"	"Oral process"	-	"Sensing approach"	"Laboratory"	-
"Meal intake"	"Jaw movement"	-	"Automatic"	"Prototype"	-
"Liquid intake"	"Ingestion"	-	"Automatically"	"Prototype"	-
"Nutrition monitoring"	"Eating activities"	-	"sensing system"	"Recognition"	-
"Diet* monitoring"	"Eating moment"	-	"sensing system"	"Recognition"	-
"Energy intake"	"Eating detection"	-	-	"Classification"	-
-	"intake gesture"	-	-	"true positive"	-
-	"food preparation"	-	-	"true negative"	-
-	"Biting"	-	-	"false positive"	-
-	"Chew"	-	-	"false negative"	-
-	"jaw motion"	-	-	"intraclass correlation"	-
-	"eating recognition"	-	-	"setting"	-
-	-	-	-	"Setup"	-
-	-	-	-	"Set-up"	-

Measurement setting: Two levels of assessment were applied to the measurement setting: (a)Artificial[14],(b)Natural[14]. (1)Controlled[14], (2)Semi-controlled[14], (3)Free[14]. They are reported in the way X(Alphabet)-Y(Number). For example, Artificial(X)-controlled(Y).

Number of participants: The total number of people that participated in the research[14].

Performance: Performance reported by the author, many of them are F1-score or accuracy[14].

2.4 Data analysis

The data from the resulting table will be used in several ways. For example, give the descriptive data on what dimension is focused on the most in 2021, and interpret what might lead to this result. Also the data of sensing principle will be collected and presented to help reader rapidly understand the field of research in 2021. Besides, the eating phase data will be collected and presented.

3 RESULTS

Figure 1 presents the systematic search and selection process following PRISMA guidelines[38].The initial literature search yielded 316 articles, all published in 2021. Following title and abstract screening, 267 articles were excluded for not meeting inclusion criteria, leaving 49 articles for full-text assessment. During full-text evaluation, 18 additional articles were excluded due to insufficient technical performance reporting (n=13), divergent research objectives (n=1), and unsuitable intended applications (n=4). The final selection comprised 31 articles containing 34 relevant studies that met all inclusion criteria for systematic analysis.

The detailed information of 31 included articles in 2021 could be referred in the Appendix A at the end of this paper.

3.1 Food intake dimensions

Regarding the dimension of food intake, eating time detection 'when' were the most widely measured parameter , with 20 of the 34 studies mentioning this dimension, counted for 59 percent of all the included articles in 2021.

While dimensions 'what' and 'how much' appeared 7 times respectively out of 34 articles, counted for 21 percent separately.

3.2 Sensing principles

Table 2. Sensing principles used for the three main aspects of food intake, when, what, and how much.

Sensing principle	When	What	How much	Total
Conductance	2	0	2	4
Motion	6	1	0	7
Sound	2	2	2	6
Spectral analysis	0	1	0	1
Strain	0	0	1	1
Vision	0	0	1	1
Combination	10	3	1	14
Total	20	7	7	34

In terms of sensing principles (Table 2), the 34 records were coded into 'conductance', 'motion', 'sound', 'spectral analysis', 'strain', 'vision' and 'combination'. Combination' was the most popular sensing principle in 2021, used in 14 of 34 studies, counted for 41 percent of all sensing approaches. Among combination methods, 'Motion' + 'Vision' was most prevalent, appearing in 7 of the 14 combination studies, counted for 50 percent of all combination approaches.

Other than sensing principle 'combination', 'motion' took the lead in single modal sensing principle, followed by 'sound' and 'conductance'. There were 7 articles in 2021 focused on the sensing principle

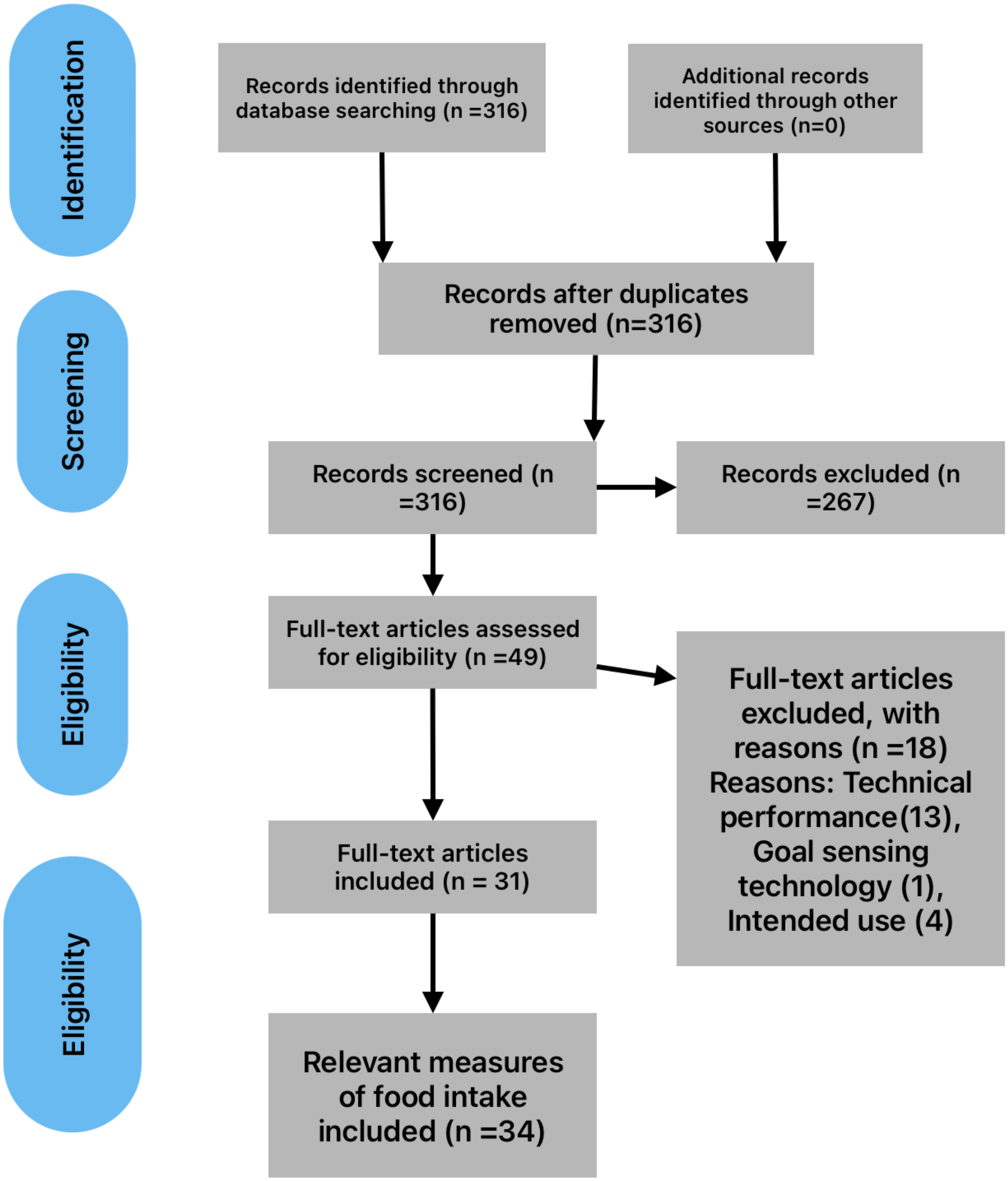

Fig. 1. Flow diagram for the scoping review process[38]

'motion', 6 articles on the sensing principle 'sound' and 4 articles on the sensing principle 'conductance'. For sensing principle 'spectral analysis', 'strain' and 'vision', they were used 1 time respectively.

In the study of 2021, no articles focused on sensing principle 'object lableling' and 'pressure'.

3.3 Sensing locations

In terms of sensing location (Table 3), 31 out of 34 studies are wearable sensors, far more than 'external' sensors, counted for 91 percent of all the researches in 2021. Sensor location 'ear' and 'face' are the most popular , have 8 out of 34 each, counted for 24 percent of the total researches in 2021 each. Sensor location 'extremeties' is also popular, there is 7 out of 34 researches focused on, counted for 21 percent of total amount of included researches in 2021. There were 4 articles measure location 'neck' and 'torso' respectively, and 3 articles measure location 'external'.

There was no studies measure the location 'intra oral' in 2021.

Table 3. Sensing locations used for the three main aspects of food intake, when, what, and how much.

Location	When	What	How much	Total
Ear	5	2	1	8
External	-	1	2	3
Extremities	7	-	-	7
Face	6	2	-	8
Neck	1	2	1	4
Torso	1	-	3	4
Total	20	7	7	34

3.4 Eating phases

Table 4. Eating phases used for the three main aspects of food intake, when, what, and how much.

Eating phase	When	What	How much	Total
Preparation	-	-	1	1
Ingestion	2	1	1	4
Oral processing	16	5	1	22
Swallowing	-	1	1	2
Digestion	1	-	3	4
Combination	1	-	-	1
Total	20	7	7	34

In terms of eating phase (Table 4), 'oral processing' stage was the most popular eating phase during the automatic food intake detection, 22 out of 34 articles focused on this stage, counted for 65 percent of the total included researches in 2021.

Regarding 'oral processing' stage, 16 out of 22 articles focused on dimension 'when', counted for 73 percent under the eating phase 'oral processing'.

There were 4 articles focused on eating phases 'ingestion' and 'digestion' respectively, 2 articles focused on 'swallowing' and 1 articles focused on 'preparation' and multiple eating phase coded as 'combination' respectively in 2021.

The combination sensing stage were eating phase 'oral processing' and 'swallowing'.

There is no studies focused on the eating phase 'conclusion' in 2021.

3.5 Sensing principles versus locations

Refer to the table 5, the sensing principles and sensor locations were measured together to give a more in depth overview.

The sensing principle 'combination' was the most widely used among all included researches in 2021, there are 14 out of 34 included articles using 'combination' principle, and it focused on the sensor location 'face', there are 6 out of 8 included articles that using 'combination' while set on the location 'face', counted for 75 percent. For sensing principle 'motion', 7 out of 34 studies focused on this principle, and 4 out of 7 were worn on extremities, counted for 57 percent.

3.6 Eating phases versus location

Refer to table 6, eating phase 'oral processing' was researched most in 2021, 22 out of 34 articles researched eating phase 'oral processing', counted for 65 percent. The sensor location were at 'ear' and 'face' the most, 8 out of 8 articles that set at the ear focused on eating phase 'oral processing', counted for 100 percent. The sensor location set for 'face', 8 out of 8 articles focused on eating phase 'sensing principle', counted for 100 percent.

3.7 Eating phases versus sensing principles

Refer to the table 7, the most used sensing principle 'combination', the most researched eating phase is 'oral processing', 22 out of 34 articles focused on 'oral processing', counted for 65 percent, and 10 out of 14 'oral processing' is the sensing principle 'combination'.

4 DISCUSSION

This systematic review analyzed 34 studies on automatic food intake detection in 2021. This analysis examined how these studies addressed the three dimensions of dietary assessment, 'when', 'what' and how much, while also investigating the sensing principles employed, eating phases focused on and the location of sensor deployed.

4.1 Synthesis of main findings

The result revealed that for all the included studies in 2021, 'when' was the predominant dimension, 20 out of 34 studies focused on 'when' dimension, counted for 59 percent in all the studies. For 'what' and 'how much' dimensions, they have 7 out of 34 respectively, counted for 21 percent respectively.

Within dimension 'when', sub-dimension 'eating or drinking recognition' was the most popular one, 15 out of 20 included studies in 2021 focused on this sub-dimension, counted for 75 percent of all studies under dimension 'when' in 2021.

The result showed that the 'oral processing' was the most popular eating phase that all included studies focused on in 2021, 22 out of 34 included studies in 2021 focused on this eating phase, counted for 65 percent of all the included studies in 2021.

The studies included in 2021 focused on 'when' dimension the most while using 'combination' sensing principle, 16 out of 22 studies using 'combination' sensing principle researches focused on 'when' dimension, counted for 73 percent of all studies under sensing principle 'combination'.

The most popular sensing locations for all included researches in 2021 were 'ear' and 'face', 8 out of 34 researches focused on sensor location 'ear' and 'face' separately, counted for 24 percent respectively. Sensor location 'extremities' is also a popular one, 7 out of 34 included researches in 2021 focused on this location, counted for 21 percent of all the studies included in 2021.

There was no included studies focused on eating phase 'conclusion' in 2021.

There was no included studies focused on sensing principle 'object labeling' and 'pressure' in 2021.

There was no included studies focused on sensor location 'intra oral' in 2021.

Table 5. Sensing principles versus the location used.

Sensing principle	Ear	External	Extremities	Face	Neck	Torso	Total
Conductance	1	-	1	-	-	2	4
Motion	1	-	4	2	-	-	7
Sound	4	-	-	-	1	1	6
Spectral analysis	-	-	-	-	1	-	1
Strain	-	-	-	-	1	-	1
Vision	-	1	-	-	-	-	1
Combination	2	2	2	6	1	1	14
Total	8	3	7	8	4	4	34

Table 6. Eating phases versus the location used.

Eating phase	Ear	External	Extremities	Face	Neck	Torso	Total
Preparation	-	1	-	-	-	-	1
Ingestion	-	2	2	-	-	-	4
Oral processing	8	-	4	8	1	1	22
Swallowing	-	-	-	-	2	-	2
Digestion	-	-	1	-	-	3	4
Combination	-	-	-	-	1	-	1
Total	8	3	7	8	4	4	34

Table 7. Eating phases versus the sensing principles used.

Eating phase	Conductance	Motion	Sound	Spectral analysis	Strain	Vision	Combination	Total
Preparation	-	-	-	-	-	1	-	1
Ingestion	-	1	-	-	-	-	3	4
Oral processing	1	6	4	1	-	-	10	22
Swallowing	-	-	1	-	1	-	-	2
Digestion	3	-	1	-	-	-	-	4
Combination	-	-	-	-	-	-	1	1
Total	4	7	6	1	1	1	14	34

4.2 Interpretation

Scoping review from McHill et al.[24] in 2020 identified that 'when did the user consume' was the primary technical challenge, that fits the result as the findings in this article, the amount of studies 'when did user eat' is more than 'what did user eat' and 'how much did user eat' for all included studies in 2021. Studies from Dashti et al.[9] also claimed that 'when' dimension is the foundational requirement for 'what' and 'how much', so the amount of studies about dimension 'when' took the lead, explaining the continued research focus on the 'when' dimension in 2021.

The predominance of sensors located around ear in 2021 studies aligns with established research on optimal sensor placement. Dashti et al.[9] demonstrated that ear-mounted sensors provide superior acoustic capture for chewing detection, which may explain why ear placement emerged as the most frequently utilized sensor location in the reviewed studies.

The prevalence of face-mounted sensors in 2021 studies can be attributed to their direct detection capabilities. Dashti et al.[9] demonstrated that facial sensor placement enables direct monitoring of chewing mechanics through temporalis muscle activity and jaw movement detection, which likely contributed to the high frequency of sensors were setting to the face in all included articles in 2021.

The predominance of eating phase 'oral processing' in 2021 research aligns with established principles in automated food intake detection. Dashti et al.[9] identified eating phase 'oral processing' as the fundamental component of automatic food intake detection, noting its advantages for non-intrusive detection methods. This technical accessibility likely explains why eating phase 'oral processing' was the most frequently studied eating phase in the systematic review.

In the systematic review, 'combination' was the most used sensing technology in 2021. Beccuti et al.[2] demonstrated that multimodal wearable technologies offer expanded possibilities for activity recognition, which likely contributed to the increased adoption of ’combination’ sensing principles took the lead in amount in 2021.

4.3 Implication

A comparison with previous research reveals evolving trends in sensing principle preferences. Haarman et al.[14] found that sensing principle ’sound’ dominated automatic food intake detection research from 2015-2020, with 68 out of 264 studies, 26 percent employing this approach. In contrast, the present 2021 systematic review identified sensing principle ’combination’ as the predominant approach, with 14 out of 34 studies, 42 percent utilizing multimodal sensing principles.

Notably, sensing principle ’sound’ remains lead to current research in amount despite this shift toward sensing principle ’combination’. Among the 14 studies employing sensing principle ’combination’, 7 studies specifically combined sensing principle ’motion’ and ’sound’. Furthermore, when examining single-modality sensing principle, ’sound’ emerged as the second most popular sensing principle after ’motion’, indicating its continued importance in the field.

The predominance of sensing principle ’combination’ in 2021 can be attributed to their superior performance capabilities. Nakamura et al.[27] demonstrated that ’combination’ sensing principles achieve significantly higher accuracy compared to single-modal approaches,for example, ’motion’ and ’vision’, which likely explains the increased adoption of ’combination’ sensing principles observed in 2021 articles.

Comparative analysis reveals both similarities and differences in eating phases of the systematic review. Haarman et al.[14] found that eating phase ’oral processing’ dominated automatic food intake detection research from 2015-2020, with 92 out of 264 studies, counted for 35 percent investigating this eating phase. Eating phase ’oral processing’ took the lead and and increased to 22 out of 34 studies, counted for 65 percent in the 2021 systematic review.

However, a notable shift occurred in the amount of eating phase ’ingestion’. While Haarman et al.[14] reported eating phase ’ingestion’ as the second most studied eating phase from 2015-2020, with 87 out of 264 studies, counted for 33 percent during the period from 2015 to 2020. Eating phase ’ingestion’ is still the second most studied eating phase in 2021, but this focus declined dramatically to only 4 out of 34 studies, counted only 12 percent. No scientific resources indicating that amount of studies focused on eating phase ’ingestion’ is declining, so this significant reduction in eating phase ’ingestion’ research may reflect the limited publication year affect the observed frequency of sensing principle ’ingestion’ in 2021.

Sensor location preferences show notable shifts between the two study periods. Haarman et al.[14] identified ’extremities’ and ’neck’ as the most frequent sensor locations from 2015-2020, with sensor location ’extremities’ appearing in 51 out of 264 studies, counted for 19 percent and sensor location ’neck’ in 50 studies, also counted for 19 percent. In contrast, the 2021 systematic review revealed ’face’ and ’ear’ as the predominant sensor locations, each appearing in 8 out of 34 studies, counted for 24 percent studies respectively.

The emergence of sensor location ’ear’ aligns with previous trends, as Haarman et al.[14] also identified that sensor location ’ear’ appeared 46 out of 264 articles in their 2015-2020 review, counted for 18 percent. However, the lead in amount of sensor location ’face’ in 2021 represents a notable shift. There is no scientific resources indicating that ’face’ is becoming popular nor other sensor location lead in amount is decreasing, so his change may reflect that involving only single year publications increases the variability and thus influence the result.

The lack of sensing principle ’object labeling’ and ’pressure’ happened in the systematic review in 2021, because in the scoping review by Haarman et al.[14] these two sensing principles were also not popular, sensing principle ’object labeling’ appeared 2 times out of 264 studies, counted for 1 percent only,there is no scientific resource that demonstrates the reason for lack of sensing principle ’object labeling’, but with a limited year and sample size, this could happen in the systematic review. For the sensing principle ’pressure’, it appeared 18 times out of 264 articles in the scoping review of Haarman et al.[14], counted for 7 percent of total articles in the period from 2015 to 2020, there is no scientific resource that demonstrates the reason for lack of sensing principle ’pressure’, but with a limited year and sample size, this could happen in the systematic review.

The lack of sensor location ’intra oral’ happened in the systematic review in 2021, in the scoping review of Haarman et al.[14] the sensor location only appeared 3 times out of 264 studies, counted for 1 percent of all articles from 2015 to 2020,there is no scientific resource that demonstrates the reason for lack of sensor location ’intra oral’, but with a limited year and sample size, this could happen in the systematic review.

Both the articles of Haarman et al.[14] and this, no studies focused on eating phase ’conclusion’ either during the period from 2015 to 2020 or 2021, there is no scientific resources that focused on eating phase ’conclusion’ in these years, so it might be too complicated or not possible to quantify the data focusing on this eating phase.

4.4 Limitation

Several methodological limitations must be acknowledged in this analysis. The focus on a single year 2021 introduces significant statistical variability, as annual fluctuations in research priorities may not reflect broader long-term trends. The distributions of dimensions, eating phases, sensor locations, and sensing principles observed in 2021 may deviate substantially from multi-year averages, as demonstrated by Haarman et al.’s[14] five-year scoping review from 2015-2020.

Additionally, this study represents a more focused subset of the broader research landscape examined by Haarman et al.[14], which may limit the findings. The smaller sample size (34 studies versus 264 studies) and narrower temporal scope may not capture the full diversity of research approaches and technological developments in automated food intake detection, potentially affecting the validity of comparative conclusions drawn between the two reviews.

5 CONCLUSION

In conclusion, the answer for the research question: "Which dimension was focused on the most in 2021,’when’,’what’ or ’how much’? ", dimension ’when’ emerged as the dominant research focus, with

20 out of 34 studies focused on ’when’ dimension, counted for 59 percent of total researches, significantly exceeding amount given to food identification ’what’ and ’how much’.

For the first sub-research question "What sensing principle was most frequently employed in 2021?", sensing principle ’combination’ predominated, utilized by 14 out of 34 studies, counted for 41 percent of all included articles in 2021. Within this category, sensing principle ’motion’ + ’vision’ are the most prevalent multimodal sensing principle, accounting for 7 out of 14 sensing principle ’combination’, counted for 50 percent of all ’combination’ sensing principle set.

Addressing the second sub-research question "What eating phases received the most research focus in 2021?", eating phase ’oral processing’ clearly dominated the research landscape, investigated by 22 out of 34 studies in 2021, counted for 65 percent of all articles, reinforcing its established importance in automated food intake detection.

6 DISCLAIMER

During the preparation of this work, I used DeepL and claude to make the article more academic. After using this tool/service, we thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome.

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A APPENDIX A

Below are the 31 included articles in total that were used in the systematic analysis in 2021.

Table 8. 31 included articles

Ref.	Author(s)	Title	Year
[22]	Konstantinos Kyritsis; Christos Diou; Anastasios Delopoulos	A Data Driven End-to-end Approach for In-the-wild Monitoring of Eating Behavior Using Smartwatches	2021
[8]	Anurag Das; Seyedhooman Sajjadi; Bobak Mortazavi; Theodora Chaspari; Projna Paromita; Laura Ruebush; Nicolaas Deutz; Ricardo Gutierrez-Osuna	A sparse coding approach to automatic diet monitoring with continuous glucose monitors	2021
[44]	M.A. Tuğtekin Turan; Engin Erzin	Domain adaptation for food intake classification with teacher/student learning	2021
[16]	Kazuhiro Hori; Fumiko Uehara; Yoshio Yamaga; Shogo Yoshimura; Jumpei Okawa; Motoki Tanimura; Takahiro Ono	Reliability of a novel wearable device to measure chewing frequency	2021

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Ref.	Author(s)	Title	Year
[31]	Vasileios Papapanagiotou; Stefanos Ganotakis; Anastasios Delopoulos	Bite-weight estimation using commercial ear buds	2021
[21]	Michael T. Knierim; Max Schemmer; Monica Perusquía-Hernández	Exploring the Recognition of Facial Activities Through Around-the-Ear Electrode Arrays	2021
[30]	Vasileios Papapanagiotou; Christos Diou; Janet van den Boer; Monica Mars; Anastasios Delopoulos	Recognition of food-texture attributes using an in-ear microphone	2021
[1]	Nooshin Bahador; Denzil Ferreira; Satu Tamminen; Jukka Kortelainen	Deep learning-based multimodal data fusion: case study in food intake episodes detection using wearable sensors	2021
[39]	Nur Asmiza Selamat; Sawal Hamid Md.Ali	Analysis of chewing signals based on chewing detection using proximity sensor for diet monitoring	2021
[18]	Md Shafiqul Islam; Tehera Hossain; Md Atiqur Rahman Ahad; Sozo Inoue	Exploring human activities using eSense earable device	2021
[36]	Seyedhooman Sajjadi; Anurag Das; Ricardo Gutierrez-Osuna; Theodora Chaspari; Projna Paromita; Laura E. Ruebush; Nicolaas E. Deutz; Bobak J. Mortazavi	Towards the development of subject-independent inverse metabolic models	2021
[32]	Projna Paromita; Theodora Chaspari; Seyedhooman Sajjadi; Anurag Das; Bobak J. Mortazavi; Ricardo Gutierrez-Osuna	Personalised meal classification using continuous glucose monitors	2021
[29]	Vasileios Papapanagiotou; Christos Diou; Anastasios Delopoulos	Self-supervised feature learning of 1D Convolutional neural networks with contrastive loss of eating detection using an in-ear microphone	2021
[41]	Nur Asmiza Selamat; Sawal Hamid Md.Ali; Khairun Nisa’ Minhad; Jahariah Sampe	Feature selection analysis of chewing activity based on contactless food intake detection	2021
[15]	Ghena M. Hammour; Danilo P. Mandic	Hearables: Making sense from motion artefacts in Ear-RGG for real-life human activity classification	2021
[34]	Nafiul Rashid; Manik Dautta; Peter Tseng; Mohammad Abdullah Al Faruque	HEAR: Fog-enabled energy-aware online human eating activity recognition	2021
[3]	Lauriane Bertrand; Nathan Cleyet-Marrel; Zilu Liang	Recognising eating activities in free-living environment using consumer wearable devices	2021
[26]	Mark Mirtchouk; Samantha Kleinberg	Detecting granular eating behaviours from body-worn audio and motion sensors	2021
[42]	Simon Stankoski; Marco Jordan; Hristijan Gjoreski; Mitja Luštrek	Smartwatch-based eating detection: Data selection for machine learning from imbalanced data with imperfect labels	2021
[40]	Nur Asmiza Selamat; Sawal Hamid Md.Ali	A novel approach for chewing detection based on temporals muscle movement using proximity sensor for diet monitoring	2021
[10]	Abul Doulah; Tonmoy Ghosh; Delwar Hossain; Masudul H. Imtiaz; Edward Sazanov	“Automatic ingestion monitor version 2” - A novel wearable device for automatic food intake detection and passive capture of food images	2021
[45]	Shuangquan Wang; Gang Zhou; Jinxiong Guan; Yongsen Ma; Zhengming Liu; Bin Ren; Hongyang Zhao; Amanda Watson; Woosub Jung	Inferring food types through sensing and characterising mastication dynamics	2021
[11]	Tonmoy Ghosh; Delwar Hossain; Abdul Doulah; Masudul H Imtiaz; Edward Sazanov	Implementing real-time food intake detection in a wearable system using accelerometer	2021

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Ref.	Author(s)	Title	Year
[48]	Zhengeng Yang; Hongshan Yu; Shunxin Cao; Qi Xu; Ding Yuan; Hong Zhang; Wenyan Jia; Zhi-Hong Mao; Mingui Sun	Human-mimetic estimation of food volume from a single-view RGB image using an AI system	2021
[35]	Philipp V. Rouast; Marc T.P. Adam	Single-stage intake gesture detection using CTC loss and extended prefix beam search	2021

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Ref.	Author(s)	Title	Year
[49]	Guanjun Zhu; Penggang Ren; Jie Hu; Junjun Yang; Yangpeng Jia; Zhengyan Chen; Fang Ren; Jiefeng Gao	Flexible and anisotropic strain sensors with the asymmetrical cost-conducting network for versatile bio-mechanical signal recognition	2021
[33]	Mahdi Pedram; Seyed Iman Mirzadeh; Seyed Ali Rokni; Ramin Fallahzadeh; Diane Myung-Kyung Woodbridge; Sunghoon Ivan Lee; Hassan Ghasemzadeh	LIDS: Mobile system to monitor type and volume of liquid intake	2021
[23]	Ki-Seung Lee	Automatic estimation of food intake amount using visual and ultrasonic signals	2021
[20]	Haruka Kamachi; Tahera Hossain; Fuyuka Tokuyama; Anna Yokokubo; Guillaume Lopez	Prediction of eating activity using smartwatch	2021
[6]	Erica R. Cohen; Mayra Lopez; Brennan M.R. Spiegel; Christopher V. Almario	Non-invasive digestion monitoring with an FDA-cleared wearable biosensor: further validation for use in tracking food ingestion	2021
[12]	Tonmoy Ghosh; Delwar Hossain; Edward Sazanov	Detection of food intake sensor's wear compliance in free-living	2021