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# Transforming food supply chains through digital tracking and monitoring technologies

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ABSTRACT

*Background:* Perishable foods with a limited shelf life are vulnerable to spoilage and may pose safety risks if distributed or stored under improper conditions. As a result, substantial amounts of food are wasted throughout distribution chains and in households. Addressing this issue requires advanced technologies for tracking products and monitoring their shelf life.

*Scope and approach:* This review examines the historical development of product tracking technologies (e.g., barcodes and QR codes) and shelf-life monitoring tools, including Time–Temperature Indicators (TTIs) and Freshness Indicators (FIs). It highlights recent efforts to integrate the two technologies, and explores emerging applications of Internet of Things (IoT) and Artificial Intelligence (AI) in supply chain management.

*Key findings and conclusions:* TTIs and FIs are effective tools for shelf-life monitoring. Their integration with product tracking systems can support traceability and real-time shelf-life assessment. Recent commercial products, such as QR-based indicators from Evigence and SpotSee, show practical use in cold chains for perishable products, including fresh produce and breast milk. However, challenges remain, including issues with data transmission, interpretation, privacy, consumer acceptance, and regulatory gaps. Addressing these challenges will need multidisciplinary collaboration in sensor development, food safety and quality, data communication, AI, consumer science, and regulation to build faster, more transparent, and efficient food supply chains.

## 1. Introduction

The food supply chain is a complex system that moves food from 'farm or catch' to 'fork' through multiple stages, including postharvest handling, processing, storage, distribution and retail, and consumption. Globally, approximately 30 % of food is lost or wasted, equal to 1.3 billion tons annually and nearly $1 trillion in value (FAO, 2025). In the United States, an alarming 40 % of the food supply is wasted, resulting in annual economic losses of $218 billion (EPA, 2025).

Various forms of food waste and loss occur at different stages in the supply chains (EPA, 2025). A major cause is the lack of effective food quality and safety monitoring systems (Nami et al., 2024). Perishable foods, such as meat, fish, dairy, and fresh produce, have short shelf life and are highly sensitive to storage conditions. Physical and biochemical changes, such as temperature fluctuation in storage and transportation, moisture loss, enzymatic activity, and lipid oxidation, reduce product quality. Microbial spoilage further accelerates deterioration, leading to discoloration, off-odors, and sliminess. Food safety concerns and the associated large-scale recalls also contribute to waste. Recent recalls involving McDonald's Quarter Pounders, Boar's Head lunch meats, and Costco smoked salmon were linked to pathogens such as *E. coli*, *L. monocytogenes*, and *Salmonella* (FDA, 2024). Large quantities of food products were removed from markets, and even unaffected items were discarded as precautionary measures. At the consumer level, household waste accounts for nearly 40 % of total food loss (USDA, 2025). A significant portion stems from the confusion over expiration date labeling. Many consumers misinterpret "sell by," "best by," and "use by" dates as safety warnings, though these labels typically reflect quality rather than safety (Cabrera, 2025). This confusion, combined with fear of foodborne illness, leads to the unnecessary disposal of still-edible food.

Advanced tracking and monitoring technologies are essential for improving food quality and safety management and reducing food waste. Historically, product tracking and shelf-life monitoring technologies were developed separately. Tracking tools such as barcodes and

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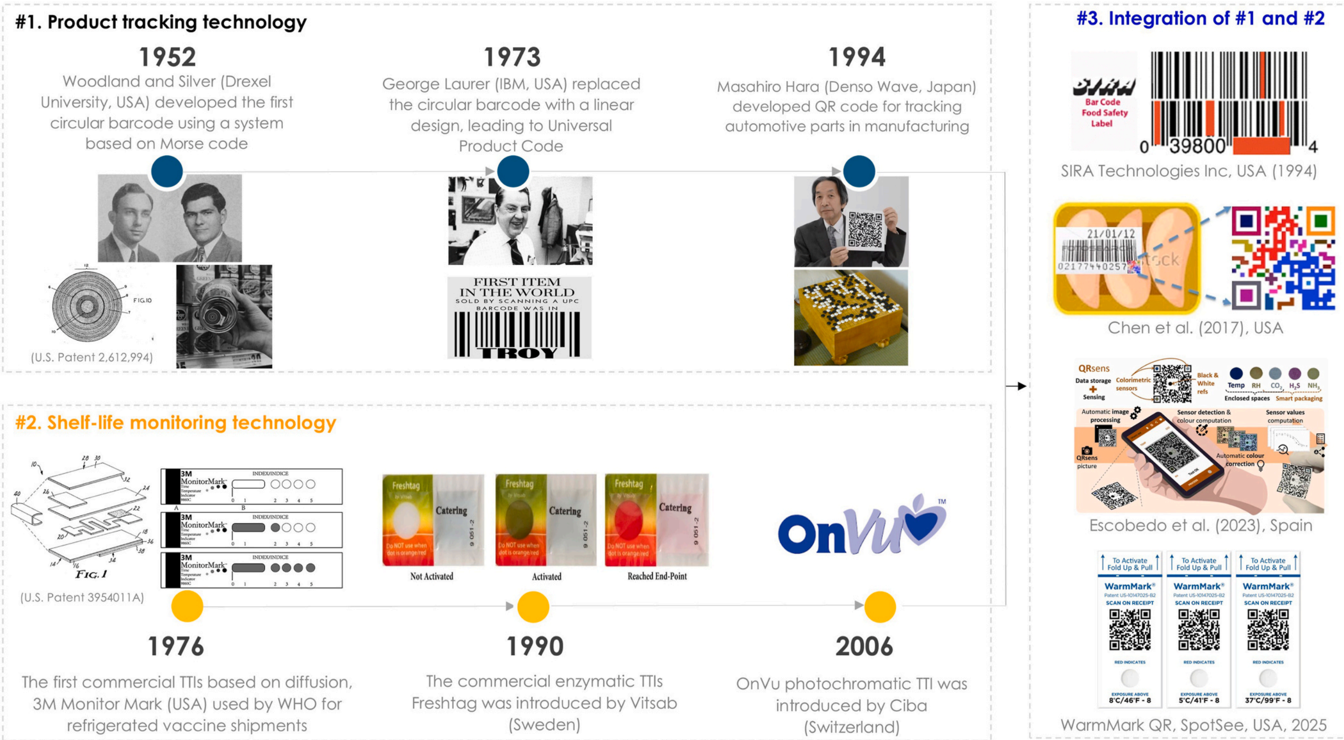


**Fig. 1.** Historical development (years) of #1 product tracking and #2 shelf-life monitoring technologies, as well as recent examples of #3 integration.

**Table 1**
Historical development of barcode and QR code technologies in food supply chains.

| Year | Technology | Milestone | Relevance to food supply chain |
|---|---|---|---|
| 1949 | First barcode | Woodland and Silver propose the circular "bull's-eye" barcode concept | Early concept for automating product identification |
| 1974 | UPC barcode | First commercial use of barcode on Wrigley's gum in Ohio, USA | Start of automated retail checkout and inventory tracking |
| 1994 | QR code | Denso Wave develops QR code for automotive part tracking | Allowed encoding of complex data |
| 2000 | QR in retail | Widespread adoption in global food logistics and inventory systems | Enabled access to origin, nutrition, and expiry information |
| 2024 | Commercial smart QR labels | QR codes are integrated with indicators (e.g., Evigence's FreshSense) | Enabled simultaneous tracking and shelf-life monitoring |

Quick Response (QR) codes have evolved over the past 70 years to support inventory control, traceability, and pricing. However, they do not provide information about food quality or safety. In parallel, shelf-life monitoring technologies such as Time–Temperature Indicators (TTIs) and Freshness Indicators (FIs) were developed to assess food quality, safety, and shelf life (Albrecht et al., 2020; Gao et al., 2020; Nami et al., 2024; Wang et al., 2015). In recent years, efforts have been made to integrate these two technologies. Fig. 1 outlines their historical evolutions and major convergence milestones (detailed descriptions of the technologies and the integration are provided in the following sections).

Based on peer-reviewed journal articles, patents, commercial reports, and regulatory documents, this review summarizes the development of tracking and monitoring technologies and examines the principles and applications of barcodes, QR codes, TTIs, and FIs. The integration of product tracking tools with shelf-life monitoring indicators (e.g., QR-based TTIs) offers a promising path toward greater traceability, enhanced safety, and more efficient, transparent supply chains. This review also discusses current challenges and explores emerging opportunities related to this integration, including the adoption of Internet of Things (IoT) and artificial intelligence (AI) in the supply chain management.

## 2. Product tracking

Product tracking technology is a key element of modern retail, logistics, and inventory management. Among the most widely used tools are barcodes and QR codes. These tools enable fast data encoding, scanning, and retrieval, supporting automate tracking and improving accuracy and efficiency across supply chains. Table 1 summarizes the historical milestones of barcodes and QR codes, and their adoptation in food supply chains.

### 2.1. Barcode

The development of product tracking methods started in the mid-20th century when early pioneers sought ways to automate inventory and checkout processes. In the 1940s, Bernard Silver and Norman J. Woodland, students at Drexel University (PA, USA) developed the first barcode concept (Woodland & Bernard, 1952). Inspired by Morse code, they designed a circular "bull's-eye" pattern that could be scanned from any angle (Fig. 1). However, this concept had major limitations due to poor printing precision, slow scanning speeds, and limited data processing capacity. In the 1970s, George Laurer, an engineer at IBM (NY, USA) introduced the Universal Product Code (UPC), a linear barcode (Fig. 1). The design was easier to print and scan, and it quickly gained adoption. In 1974, a pack of Wrigley's gum became the first product scanned at a retail checkout using a UPC code in Ohio, USA. The success of the UPC system transformed inventory and logistics operations worldwide.

Barcodes represent data as a series of black and white bars. The most

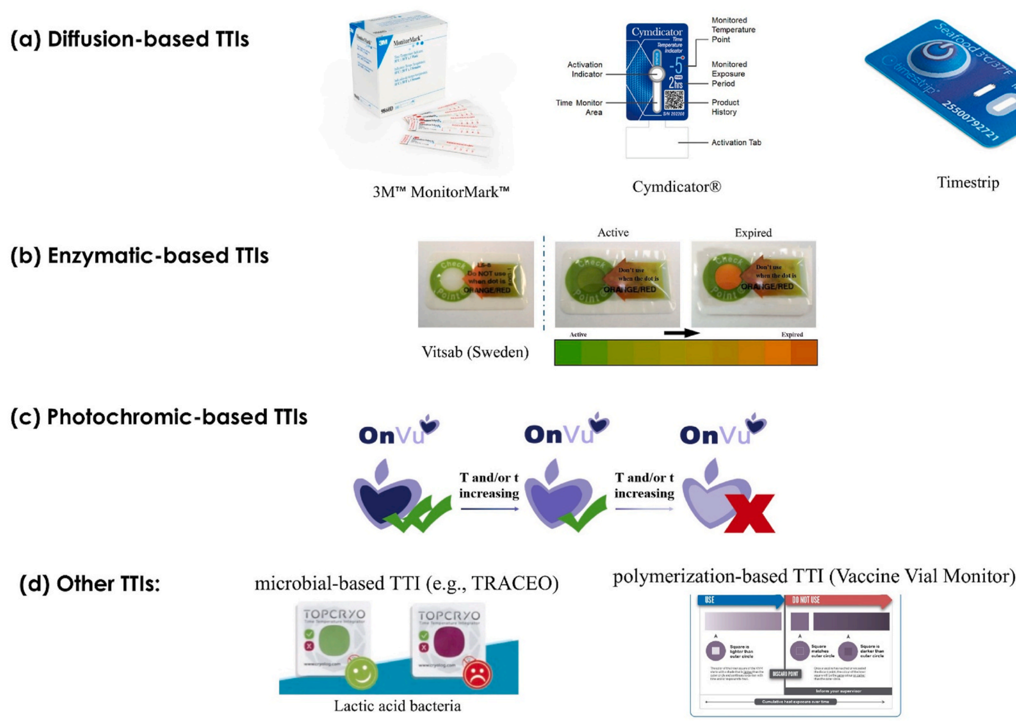


**Fig. 2.** Classification of time-temperature indicators (TTIs) and commercial TTIs.

common type, UPC, consists of 12 numerical digits encoded as bar patterns (Fig. 1). Variants include EAN, Code 39, and Code 128 (Wartenberg & Snyder, 2003). In action, a laser scanner detects light reflected from the barcode's surface and converts it into an electrical signal. The signal is processed into a digital number, which links to a central database for product identification, pricing, and inventory control.

### *2.2. QR code*

As global supply chains grew more complex during the 1990s, industries needed tracking tools that could store more data than traditional barcodes. The UPC, for example, can only encode up to 12 digits and lacks features such as error correction or encryption. In response, Masahiro Hara of Denso Wave, Japan, developed the QR code in 1994, inspired by the board game Go (Fig. 1). Originally designed for tracking automobile parts, this two-dimensional code soon expanded into retail, logistics, ticketing, payments, and food labeling.

The largest version of QR Codes (Version 40) encode 7089 digits, 4296 letters, and 2953 binary data (Gao, Prakash, & Jagatesan, 2007). Each QR code consists of an array of black and white square modules that represent binary data. Key QR code features include: (1) finder patterns (three large squares at the corners) to help scanners locate and orient the code, (2) alignment patterns that correct for distortion on curved surfaces, (3) timing patterns (alternating modules between finder patterns) that define the grid's structure, (4) quiet zone (a blank margin) that separates the code from surrounding graphics, and (5) data area that stores the actual information using binary encoding (Tiwari, 2016). QR codes also include Reed-Solomon error correction (Wicker & Bhargave, 1999), which allows data recovery even if up to 30 % of the code is damaged. This feature ensures readability in cases where the QR code is partially obscured, smudged, or distorted.

QR codes are scanned using camera-based devices such as smartphones or handheld readers. The image is processed by algorithms that detect, align, and decode the data. Their fast and reliable scanning capabilities make QR code widely used for digital payments, authentication, product tracking, and consumer engagement.

## 3. Food shelf-life monitoring

TTIs and FIs were developed to monitor the quality and safety of perishable products during storage and distribution (Gao et al., 2020; Ghaani, Cozzolino, Castelli, & Farris, 2016). TTIs estimate remaining shelf life based on a product's time–temperature history, while FIs detect food spoilage more directly by responding to chemical or microbial changes, often reflected in pH. The choice between TTIs and FIs depends on dominant spoilage or quality degradation mechanisms of specific food products. In some cases, both indicators can be used; in others, one may be more suitable. For example, pH-based FIs are commonly used for refrigerated meat and fish, where microbial activity produces volatile basic compounds (e.g., ammonia), causing measurable pH shifts. TTIs are more effective for foods where temperature control is critical, such as fresh produce, dairy, and frozen foods. The following sections will describe the basic principles, types, and applications of different TTIs and FIs.

### *3.1. Time-temperature indicators (TTIs)*

TTIs are designed to reflect the cumulative thermal exposure of a product over time. TTIs do not provide real-time temperature readings. Instead, TTIs integrate time–temperature history and translate it into a visual signal—typically a color change caused by chemical or enzymatic reactions or material diffusion (Taoukis, 2001). The concept of TTIs dates back to the 1970s. In 1976, 3M (USA) introduced the first commercial diffusion-based TTI, known as Monitor Mark (Fig. 2a) (Manske, 1976). The World Health Organization later adopted this TTI for monitoring vaccines in cold chains (Taoukis, 2001). Since then, more TTIs based on different mechanisms have been developed. For example, in 1990, Vitsab International AB (Sweden) introduced an enzymatic TTI (Fig. 2b), and in 2006, Ciba Specialty Chemicals (Switzerland) developed photochromic OnVu™ TTIs (Fig. 2c).

The fundamental principle behind TTIs is that their response kinetics, such as rate of color change are designed to correspond with microbial growth or quality loss in foods. The changing rates of both TTI color and food quality are typically temperature dependent and often

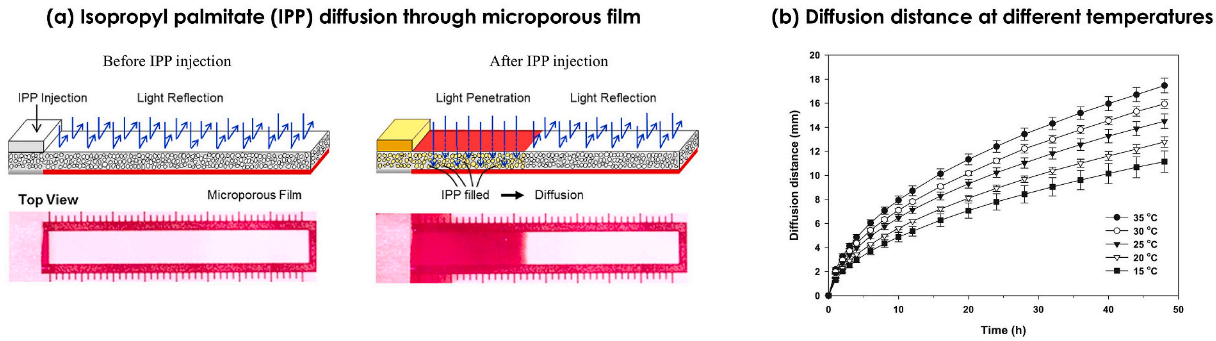


**Fig. 3.** (a) Principle of diffusion-based TTI and (b) temperature-dependent diffusion kinetics (Kim et al., 2016).

modeled using the Arrhenius equation (Gao et al., 2020). For more complex chemical reactions that do not follow fixed order kinetics, that is, where the isothermal rate constant is a function of both temperature and time, other non-linear kinetics models, such as Weibull, Logistic, or Gompertz can be utilized. Readers are advised to consult previous publications (e.g., Peleg, Normand, & Corradini (2012), Peleg and Saguy (2024), Peleg (2024) and Peleg et al. (2017)) on this topic.

In most chemical and enzymatic reactions in food systems, the experimentally obtained parameters in the Arrhenius relationship apply only within a relatively narrow range around a selected reference temperature. Thus, a revised Arrhenius equation is often used:

$$k = k_{ref} \cdot e^{-\frac{E_a}{R}\left[\frac{1}{T}-\frac{1}{Tref}\right]} \quad (1)$$

or in logarithmic form:

$$\ln(k) = \ln(k_{ref}) + \left(-\frac{E_a}{R}\right)\cdot\left[\frac{1}{T}-\frac{1}{T_{ref}}\right] \quad (2)$$

where $k_{ref}$ is the rate constant at the reference temperature, $E_a$ is the activation energy (kJ/mol), $R$ is the universal gas constant (8.314 J/K·mol), and $T$ and $T_{ref}$ are the absolute and reference temperature (K), respectively.

TTIs should be calibrated before use. The $E_a$ of a TTI should closely match either that of the chemical or microbial reactions occurring in foods (Taoukis & Labuza, 2003). The closer the match, the more accurate the TTIs are. A general guideline is that the difference should be less than 25 kJ/mol (Taoukis & Labuza, 2003):

$$\left|E_{a_{food}} - E_{a_{TTI}}\right| \ll 25\,\frac{kJ}{mol} \quad (3)$$

TTIs are typically categorized by their sensing mechanisms, namely, diffusion, enzymatic, photochromic, chemical, or other reactions (Fig. 2).

#### 3.1.1. Diffusion-based TTIs

Diffusion-based TTIs use temperature-dependent migration of a substance—such as a dye, ester, or polymer—through a porous medium (Fig. 3a and b). The process generally follows Fick's law:

$$\frac{\partial C}{\partial t} = D\frac{\partial^2 C}{\partial x^2} \quad (4)$$

where $C$ (mol/m$^3$) is the concentration of the diffusing species, $t$ is time (s), $D$ (m$^2$/s) is the diffusion coefficient (depending on temperature), and $x$ (m) is the distance through which diffusion occurs.

The diffusion coefficient $D$ often follows the Arrhenius equation:

$$D = D_0 e^{\left(-\frac{E_a}{RT}\right)} \quad (5)$$

where $D_0$ is the pre-exponential factor (m$^2$/s), $E_a$ is the activation energy for diffusion (J/mol), and T is absolute temperature (K).

The 3M Monitor Mark (U.S. Patent 3,954,011) was one of the earliest commercial examples. It used a fluid pad, a wick, and an indicator strip to display color changes as material migrated through the wick. Once the separator was removed, the indicator activated. This concept was later improved into Freshness Check™ (Arens et al., 1997). Shimoni, Anderson, & Labuza (2001) evaluated seven Freshness Check TTIs, and found that the response of the TTIs under isothermal conditions followed Arrhenius kinetics. The $E_a$ of the tested TTIs ranged between 96 and 130 kJ/mol, which were close to those of spoilage microorganisms, such as 76 kJ/mol for *Pseudomonas fragi* in skim milk and 82 kJ/mol for *Pseudomo-nas spp* for chilled fish. More recent commercial diffusion-based TTIs include Timestrip® (Timestrip UK Ltd, Cambridge, UK) and Cym-Dicator® (Cymmetrik Enterprise Co., Ltd, Taiwan (Fig. 2a).

#### 3.1.2. Enzymatic TTIs

Enzymatic TTIs are designed based on temperature-sensitive enzyme-catalyzed reactions (Rönnow, 2016; Tsironi et al., 2017). A typical example involves lipid hydrolysis in which enzymes break lipids into fatty acids and glycerol. This triggers a pH change that causes a color shift in a pH-sensitive indicator (Gurunathan, 2024; Pandian, Chaturvedi, & Chakraborty, 2021).

Vitsab (Vitsab International AB, Sweden) is a well-known and widely used commercial enzymatic TTI (Fig. 2b). It consists of a lipid substrate, a lipase enzyme, and a pH-sensitive color indicator. Activation occurs by breaking the barrier between the lipid and enzyme, allowing the lipase to initiate hydrolysis. The resulting fatty acid production lowers the pH, leading to a progressive color change of the pH-indicator that reflects cumulative temperature exposure. The lipase enzyme and lipid substrate are carefully selected in the design of enzymatic TTIs for a specific food product. Tsironi, Ronnow, Giannoglou, & Taoukis (2017) evaluated the performance of two Vitsab TTIs for monitoring the growth of *Vibrio parahaemolyticus* and *Vibrio vulnificus* in oysters. In this study, two types of Vitsab enzymatic TTIs were tested: (1) LP-type and (2) S-type. The LP-type TTI utilizes Rhizopus oryzae lipase to hydrolyze a lipid substrate composed of trilaurin and tripalmitin. The S-type TTI employs a lipid substrate composed of 75 % methylstearate and 25 % trilaurin. To match the growth kinetics of *Vibrio* spp., different enzyme concentrations and lipid substrate compositions were used. Vitsab TTIs have also been used to monitor the safety and quality of airline meals. Airline meals are prepared in advance and stored prior to loading. Flight delays could lead to extended storage and possible temperature abuse, increasing the risk of pathogen growth. British Airways implemented Vitsab TTIs to track onboard meal safety and monitor the potential growth of such as *Listeria monocytogenes*, *Bacillus cereus*, and *Staphylococcus aureus* (Rönnow, 2016).

In addition to Vitsab, other enzymatic TTIs have been developed using enzymes such as amylase, laccase, and urease. For example, Kim, Kim, & Lee (2012) developed a laccase-based TTI and found that laccase oxidation reactions produced temperature-dependent discoloration. Wu

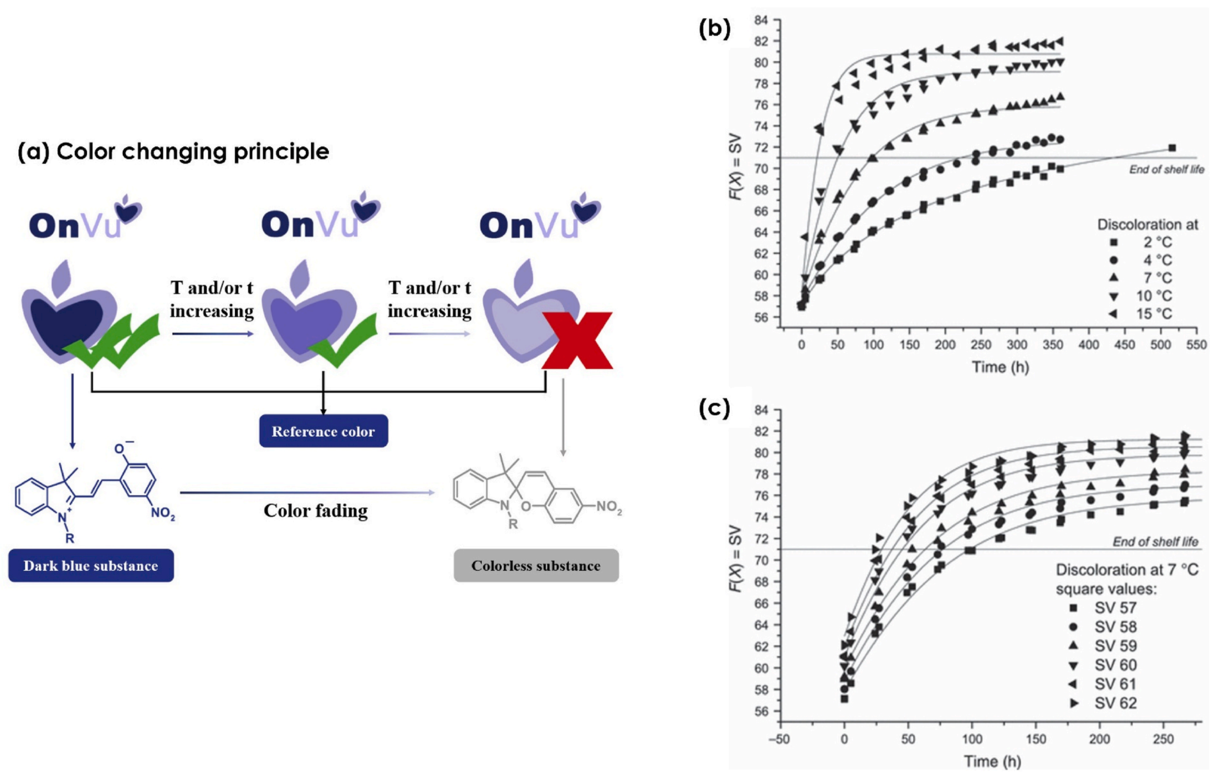


**Fig. 4.** (a) Principle of photochromic OnVu TTI, color changing kinetics at (b) different temperatures, and (c) different UV charging times (Kreyenschmidt et al., 2010).

et al. (2015) investigated TTIs using *Aspergillus niger* lipase and reported that the activation energy of the TTIs (31.6–42.1 kJ/mol) matched with that of certain fresh produce, seafood, and dairy products.

### 3.1.3. Photochromic-based TTIs

Photochromic-based TTIs use light-sensitive compounds that undergo structural changes upon exposure to light and temperature. A common example is spiropyran which reacts to ultraviolet (UV) light by changing from a closed-ring (colorless or lightly tinted) to an open-ring (deep blue or purple) structure (Fuchs & Carrigan, 2013). This transformation creates a merocyanine molecule with high conjugation, responsible for the visible color (Fig. 4a). Once activated by UV light (typically 365 nm), the color intensity of the dye gradually fades as it reverts to its original form. This fading is temperature-dependent and follows Arrhenius kinetics. To prevent unintentional recharging or premature fading during handling or storage, a UV filter is typically applied over the photochromic-based TTIs.

A well-known commercial application of this technology is the OnVu™ TTI. Fig. 4 shows how a typical OnVu™ TTI responded under different conditions (Kreyenschmidt et al., 2010). The color fading was quantified using the square value (SV):

$$SV = \sqrt{(L^2 + a^2 + b^2)} \tag{6}$$

where $L$, $a$ and $b$ are lightness, red and green components, respectively.

As shown in Fig. 4b, SV values increased more rapidly at higher temperatures, following Arrhenius relationship (Kreyenschmidt et al., 2010). Fig. 4c also shows that longer UV charging times produced higher initial SV values and extended the response period, as more time was needed for the dye to fade. The activation energy for the discoloration process was reported to range from 92 to 106 kJ/mol, depending on UV exposure duration (550–1600 ms).

Traditional evaluation of TTI color change relies either on visual inspection or the use of instruments such as colorimeters and spectrophotometers. Visual assessment involves comparing the label color to a reference chart, making the process subjective and prone to inconsistency. In contrast, colorimeters and spectrophotometers provide objective and accurate measurements but require controlled lighting conditions and regular calibration. These limit their practicality for routine use in supply chains. A smartphone-based app to evaluate OnVu™ TTI color changes was developed by Waldhans et al. (2023). The app captured images using the phone camera and applied color calibration. It then analyzed the remaining shelf life based on color changes. This Android-based mobile system was tested for raw pork sausage (Waldhans et al., 2024) and ready-to-eat salads (Waldhans, Albrecht, Ibald, Wollenweber, & Kreyenschmidt, 2025).

### 3.1.4. Chemical-reaction based TTIs

Chemical reaction-based TTIs utilize irreversible chemical reactions such as Maillard browning, doping reactions, or oxidation (Wang et al., 2015). Among these, Maillard reaction-based TTIs have been mostly studied. Hu et al. (2020) developed TTIs using lysine and xylose to detect the formation of fluorescent advanced glycation end products (AGEs) in reheated foods. Three formulations—TTI-1, TTI-2, and TTI-3—varied in xylose concentration (0.3 M, 0.4 M, and 0.5 M), while lysine concentration remained constant at 0.4 M. The discoloration followed temperature-dependent kinetics, with activation energies ranging from 83.6 to 96.2 kJ/mol. Among the three, TTI-1 was the most effective for detecting AGE formation in instant soymilk powder. Sakai et al. (2020) developed a Maillard reaction-based TTI for chilled, vacuum-packed beef. The system used D-xylose, glycine, and disodium hydrogen phosphate as main components. These components were packaged separately and mixed to initiate the color reaction. Two formulations were developed to suit different storage durations. Similarly, Cho and Lee (2022) tested a D-xylose and glycine-based TTI on cold-stored strawberries. TTI color changes correlated well with weight loss, color change, and appearance damage of strawberries at 1 °C, 4 °C, and 7 °C.

#### 3.1.5. Other TTIs

In addition to the major categories discussed above, several other types of TTIs have been developed, including microbial, polymerization-based, nanoparticle-based, and electronic systems (Gurunathan, 2024; Nami et al., 2024). Microbial TTIs function by utilizing the growth and metabolism of live microorganisms. Typically, microbial TTIs include: (1) spoilage or non-pathogenic bacteria (e.g., lactic acid bacteria), (2) a nutrient-rich growth medium (e.g., Tryptic Soy Agar), and (3) a pH-sensitive indicator (Mataragas et al., 2019). As the bacteria grow, they produce organic acids that lower the pH, causing color change. A commercial example is Cryolog's TRACEO® microbial TTI (Fig. 2d), which uses lactic acid bacteria to monitor temperature abuse in seafood and meat products. The effectiveness of microbial TTIs depends on proper matching with the spoilage kinetics of the target food. This involves selecting appropriate microbial strains, growth media, and environmental conditions. For example, Mataragas et al. (2019) developed a microbial TTI using *Janthinobacterium* sp., a psychrotrophic bacterium that produces violacein. The activation energy of this TTI was adjusted by modifying medium pH, initial bacterial concentration, and inoculation volume to match the spoilage kinetics of beef.

### 3.2. Freshness indicators (FIs)

Spoilage of perishable foods often involves microbial activity, enzymatic degradation, and biochemical processes that alter pH (Ghaani, Cozzolino, Castelli, & Farris, 2016; Nami et al., 2024). FIs detect pH changes to indicate product freshness or degradation. Understanding how pH values change in each food category is essential for designing or selecting appropriate FIs.

#### 3.2.1. Meats

Fresh meat typically has a pH between 5.4 and 5.8, depending on animal species, muscle type, and pre-slaughter conditions (Borch et al., 1996). After slaughter, glycolysis of muscle glycogen produces lactic acid which lowers the muscle tissue pH to around 5.5 during rigor mortis. In storage, microbial activity shifts the pH, depending on dominant microorganisms and storage conditions. Under aerobic storage, *Pseudomonas* spp. dominate (Nychas et al., 2008). These bacteria initially consume glucose and later break down amino acids, generating amines and ammonia, which raises pH above 6.5 and causes slime formation, discoloration, and off-odors (Casaburi et al., 2015). Enterobacteriaceae and *Shewanella putrefaciens* also contribute to spoilage by producing sulfur compounds and ammonia (Nychas et al., 2008). In vacuum-packed or modified atmosphere packaging (MAP) storage, lactic acid bacteria (e.g., *Lactobacillus* spp., *Carnobacterium* spp., *Leuconostoc* spp.) dominate. These bacteria ferment sugars into lactic and acetic acids that lower pH and create sour odors (Borch et al., 1996). Proteolytic activity from endogenous and microbial enzymes can also change pH by releasing ammonia and amines from muscle proteins (Borch et al., 1996).

#### 3.2.2. Fish

Fish spoilage is primarily caused by microbial activity, enzymatic autolysis, and lipid oxidation (Ghaly et al., 2010). Among these, microbial metabolism is the main factor affecting freshness and shelf life of fish (Gram and Huss, 1996; Zhuang et al., 2021). The specific spoilage microorganisms differ depending on the fish species, their habitats, and storage conditions. In oxygen-rich storage conditions, such as fresh fish stored on ice, *Pseudomonas* spp. and *Shewanella putrefaciens* are typically the dominant spoilage bacteria. *Pseudomonas* spp. degrade proteins and lipids, producing aldehydes, ketones, esters, and sulfur compounds that contribute to fruity or putrid odors (Zhuang et al., 2021). *Shewanella putrefaciens* utilize trimethylamine oxide (TMAO) as an electron acceptor, converting it into trimethylamine (TMA), which produces the characteristic ammonia-like fishy odor. Under vacuum or modified-atmosphere storage, the microbial ecology shifts. The spoilage of marine fish is primarily due to *Photobacterium phosphoreum*, a $CO_2$-resistant bacterium that rapidly converts TMAO to TMA. Freshwater and tropical fish are more prone to spoilage under the influence of lactic acid bacteria, which produce organic acids and cause acidic off-odors (Gram and Huss, 1996). Enzymatic autolysis and lipid oxidation can also contribute to fish spoilage (Nie et al., 2022). Enzymatic autolysis starts after fish die as proteins degrade, muscle structure weakens, and flesh loses water, leading to softness. This process produces off-flavors and a strong fishy smell as TMAO converts to TMA. Lipid oxidation occurs when fats react with oxygen, which results in rancid odors, discoloration, and nutrient loss.

These spoilage pathways often result in measurable pH changes due to the accumulation of alkaline metabolites such as ammonia, TMA, and other volatile amines. For example, the pH of tilapia stored at 4 °C increased from 6.9 to 8.6 within six days (Yan et al., 2021). Chinese white shrimp and Redlip croaker stored at 28 °C experienced pH increases from 6.4 to 7.6 and from 6.0 to 7.2, respectively, within 24 h (Khan et al., 2024). Similarly, *Chub mackerel*, *Spanish mackerel*, and *Largehead hairtail* stored at 4, 10, and 20 °C showed pH increases from 6.0 to between 6.2 and 7.0 over seven days (Kim, Park, and Shin, 2023). Due to the strong correlation between pH changes and fish spoilage, pH is widely used to assess fish freshness and shelf life (Abbas et al., 2008).

#### 3.2.3. Dairy products

Fresh milk typically has a pH of 6.6–6.8. Microbial activities can cause either acidification or alkalization depending on spoilage organisms (Ledenbach & Marshall, 2009). Lactic acid bacteria, such as *Lactobacillus* and *Streptococcus*, ferment lactose into lactic acid which reduces pH. This acidification leads to sour flavors, coagulation, and curdling, which are the characteristic signs of spoilage in milk and yogurt (Poghossian, Geissler, & Schöning, 2019). Heterofermentative bacteria also contribute to spoilage by producing acetic acid, ethanol, and $CO_2$ (Martin et al., 2021). In contrast, proteolytic and psychrotrophic bacteria, such as *Pseudomonas* spp., degrade milk proteins, releasing ammonia and biogenic amines. This results in pH increases, leading to bitterness, sliminess, and discoloration—particularly in refrigerated milk, fresh cheeses, and butter (Ávila et al., 2025). Heat-resistant proteases from *Pseudomonas* and *Bacillus* can even spoil pasteurized or UHT-treated milk (Ledenbach & Marshall, 2009).

In soft and ripened cheeses, pH changes result from microbial succession. Surface-ripening molds and bacteria metabolize lactic acid, raising pH, while interior fermentation continues to lower pH (Martin et al., 2021). Gas-producing bacteria such as *Coliforms* and *Leuconostoc* can also cause pH shifts, leading to bloating and texture defects (Poghossian, Geissler, & Schöning, 2019). In summary, acidification is typical in fermented dairy products, driven by lactic acid fermentation, whereas alkalization occurs more frequently in protein-rich dairy items subject to spoilage by proteolytic bacteria.

#### 3.2.4. Fruits and vegetables

Fruits generally have an acidic pH due to their high organic acids, such as citric, malic, and ascorbic acids. During spoilage, pH may vary depending on microbial activity. In many sugar-rich fruits (e.g., berries, citrus), spoilage often leads to acidification as yeasts and lactic acid bacteria ferment sugars into organic acids (Barth et al., 2009). For example, glucose fermentation by *Lactobacillus* leads to lactic acid accumulation, which lowers the pH and contributes to sour flavors. *Penicillium* species can also contribute to acidification through citric acid production, particularly in citrus fruits. In contrast, some bacterial metabolism results in the production of basic compounds such as ammonia and amines, which cause pH increase. This process occurs when spoilage bacteria degrade proteins or amino acids in overripe fruits. Species of *Pseudomonas* are known to break down amino acids in tropical fruits such as bananas, leading to a slight increase in pH (Alegbeleye, Odeyemi, Strateva, & Stratev, 2022).

Vegetables, on the other hand, generally have higher initial pH

**Table 2**
Summary of food freshness indicators and related applications.

| Foods | Sensor materials | Sensor detection and Transmission | Unique features/ applications | References |
|---|---|---|---|---|
| **Meat** | | | | |
| Chicken | Optical vapor-sensitive dyes printed on paper | Smartphone reads color information from QR code to detect spoilage | Transforms QR into real-time freshness indicators via smartphone scanning | Chen et al. (2017) |
| Minced beef | Alizarin in cellulose-chitosan film | Film changes from yellow to brown to purple as TVB-N increases, correlating with spoilage | Strong correlation with TVB-N, a major spoilage biomarker | Ezati et al. (2019) |
| Chicken | 20 types of chitosan-dye porous nanocomposites | Deep CNN model trained on barcode images achieves 98.5 % accuracy in freshness prediction | Smartphone-compatible barcode system and AI model for real-time freshness monitoring | Guo et al. (2020) |
| **Fish and Seafood** | | | | |
| Codfish | Bromophenol blue, bromocresol green | Strip changes color from yellow to blue as $NH_3$ increases | "Progress bar" concept visually indicates food freshness | Wang et al. (2022) |
| Shrimp | Purple sweet potato extract | Paper changes from pink to green as shrimp releases volatile amines. The hidden word "BAD" appears as spoilage progresses | Text-based spoilage warning | Wangmo et al. (2022) |
| Trout, salmon | Saffron and barberry anthocyanins in gelatin/chitin nanofibers | Color change from pink to yellow and violet to green as spoilage progresses | Real-time visual freshness indication | Khezerlou et al. (2023) |
| Crucian, mackerel, salmon | Gelatin-based edible film with blueberry anthocyanins | pH and $NH_3$-responsive color change; reduces TVB-N by 60.8 % | Freshness monitoring with antioxidant and antibacterial properties | Pan et al. (2023) |
| Redlip croaker and Chinese white shrimp | Carbon quantum dots with pH indicator | aper-based sensor changes from yellow to brown with increasing TVB-N levels | Carbon quantum dots provide high sensitivity and broad detection range | Khan et al., 2024 |
| Cod, tilapia | Hibiscus flower anthocyanins | Colorimetric paper changes color based on pH variation due to ammonia release. | Cost-effective, natural dye-based freshness sensor | Dubey et al. (2024) |
| **Fresh produce and Milk** | | | | |
| Fresh-cut bell peppers | Methyl red + bromothymol blue | Indicator turns from yellow-green to orange as $CO_2$ increases | An indicator specifically designed for fresh-cut vegetables | Chen et al. (2018) |
| Strawberry | pH-sensitive film | Color change with pH shift | Visual indicator for spoilage under cold storage | Cho & Lee (2022) |
| Pasteurized milk | Anthocyanins from black carrot | Film changes color from pink to khaki with pH increase, indicating milk spoilage. Remains stable for 1 month at 20 °C | Uses natural anthocyanins for food-grade, biodegradable freshness monitoring | Tirtashi et al. (2019) |

values than fruits. Due to microbial degradation of proteins or amino acids, alkalization is common during vegetable spoilage. Bacteria such as *Pseudomonas, Erwinia*, and *Bacillus* hydrolyze amino acids and release ammonia and other alkaline byproducts (Barth et al., 2009). For example, *Erwinia carotovora* that causes soft rot in carrots increases pH due to ammonia production. Similarly, *Pseudomonas fluorescens* and *Bacillus* species degrade proteins in leafy greens, increasing the pH while also causing a slimy texture. Although less common, acidification can also occur in vegetables due to fermentative bacteria. In vegetables such as cucumbers and leafy greens, lactic acid bacteria ferment carbohydrates and lower pH. Spoilage fungus such as *Geotrichum candidum* can also acidify soft vegetables (e.g., tomatoes and onions) by producing organic acids (Alegbeleye et al., 2022).

Once fruits and vegetables are cut or processed, their pH behaviors change due to greater exposure to oxygen and microorganisms (Barth et al., 2009). In cut fruits such as apples and bananas, enzymatic browning caused by polyphenol oxidase (PPO) can produce acidic compounds, which may lower the pH. In contrast, cut vegetables such as lettuce and spinach often experience pH increases. This is due to rapid microbial growth—particularly by *Pseudomonas* and *Enterobacter*—which release ammonia and other alkaline substances on exposed surfaces.

### 3.2.5. Developments of FIs

Given the strong relations between pH and spoilage of perishable foods discussed above, different pH-sensitive FIs were developed. Table 2 summarizes recently developed FIs, their detection principles, and unique features and applications. For example, Ezati, Tajik, & Moradi (2019) and Taherkhani et al. (2020) designed pH-sensitive indicators for beef using colorimetric films that respond to microbial-induced pH shifts. The studies reported that beef pH increased during storage due to accumulation of ammonia, TMA, and total volatile basic nitrogen (TVB-N). Ezati et al. (2019) proposed an indicator by embedding alizarin in a cellulose-chitosan film, which changed from yellow to brown to purple as pH increased. Taherkhani et al. (2020) developed a grape anthocyanin-based indicator in bacterial nanocellulose (BNC), which shifted from red to purplish-red to blue as spoilage progressed.

Early FIs typically used single pH-sensitive dyes. But the single-dye FIs had several limitations, such as narrow pH detection range, abrupt color changes at specific pH threshold, and limited precision. To address these limitations, newer multi-dye FIs have been developed. Chen et al.


**Fig. 5.** QR-based sensor platforms: (a) FreshSense™ (Evigence, https://www.evigence.com/), and (b) Dr. Talbot's MilkFresh (https://drtalbots.com/).

(2017) used three pH-sensitive dyes—Methyl Red, Nile Red, and Zinc Tetraphenylporphyrin (Zn-TPP) microbeads—to assess chicken freshness by detecting pH changes and volatile organic compounds (VOCs). The sensor showed different color changes at different spoilage stages. Chen et al. (2018) developed a colorimetric indicator label for packaged fresh-cut green bell peppers. The indicator combined methyl red and bromothymol blue in a 3:2 ratio, resulting in a visible color shift from yellow-green to orange as $CO_2$ levels increased during storage. Wang et al. (2022) introduced a "progress bar" colorimetric strip sensor array using bromophenol blue (BPB) and bromocresol green (BCG) in varying concentrations. The design facilitated a gradual transition from yellow to blue as ammonia levels rose. Ammonia concentration was quantified by counting the number of colored spots.

More advanced approaches combine sensor arrays with machine learning. Guo et al. (2020) developed a barcode-based sensor platform incorporating 20 dye-loaded chitosan nanoparticles in a cellulose acetate film. Each dye responded differently to spoilage gases, generating a unique color pattern. A deep convolutional neural network (DCNN), trained on 3475 labeled samples, achieved 98.5 % accuracy in predicting meat freshness.

## 4. Integration of product tracking and shelf-life monitoring

The concept of integrating tracking and monitoring functions dates back to 1994, when Sira Technologies (CA, USA) developed a barcode system with a toxin-sensitive indicator (Goldsmith, 1994). Upon exposure to pathogens, such as *Salmonella*, *Listeria*, and *E. coli*, the indicator triggered a change that rendered the barcode unreadable or unscannable (Fig. 1 #3).

Recent advances focus on incorporating TTIs or FIs into QR codes. For example, Chen et al. (2017) developed a pH-responsive QR code by embedding resin microbeads containing colorimetric dyes into a paper substrate. The beads changed color in response to spoilage-related volatile compounds. A smartphone algorithm processed the color data during scanning to estimate freshness. This method enables simultaneous product identification and quality monitoring through a single scan. Escobedo et al. (2023) proposed a concept called QRsens, a platform that integrated multiple sensors within a QR code format. In QRsens, traditional finder patterns were replaced with sensors, and the central area included two reference markers for color calibration. A custom mobile app was developed to scan the QR code, extract encoded data, and interpret sensor signals. According to the authors, QRsens concept was designed for two main applications: (1) smart packaging that detects food spoilage by measuring $NH_3$ and $H_2S$ levels, and (2) enclosed space monitoring for $CO_2$ leakage in systems such as modified atmosphere packaging (Fig. 1 #3).

Commercial systems based on this integration have recently entered the market. In 2024, Evigence (Israel) launched a freshness management platform that combines QR codes with TTIs (Fig. 5). The system, branded as FreshSense, allows users to scan QR codes on packages to assess freshness information derived from TTIs. Data is uploaded to a cloud platform for shelf-life prediction. FreshSense has been applied in cold chains for fresh produce (e.g., strawberries) (Fig. 5a) and for breast milk via a collaboration with Dr. Talbot's (Evigence, 2025). Another commercial system, WarmMark QR (U.S. patent 10147025-B2), was introduced by SpotSee (USA) in 2025 (Fig. 1 #3). WarmMark QR integrated TTI with QR code. Mobile devices scan the code to identify the indicator and read its status. According to SpotSee, WarmMark QR is applicable for pharmaceuticals, medical supplies, perishable foods, and temperature-sensitive electronics such as semiconductors.

The integration mechanisms for these commercial systems (e.g., how to print TTIs on QR code) are quite vague, as the designs and the main components are proprietary and not publicly disclosed due to confidentiality or pending patents. At the time of writing, very few peer-reviewed papers are available on this topic (Ecker & Pretsch, 2014; Hakola et al., 2021). This gap highlights the need for future research to explore, validate, and standardize integration methods.

## 5. Consumer interactions

TTIs have been studied for over 40 years (Arens et al., 1997; Taoukis & Labuza, 2003; Nami et al., 2024). Despite their potential benefits to manufacturers, retailers and consumers, the adoption of TTIs has been limited due to added cost, regulatory uncertainties, and stakeholder mistrust (Ghaani, Cozzolino, Castelli, & Farris, 2016; Sohail, Sun, & Zhu, 2018; Waldhans et al., 2024). A general lack of consumer knowledge and limited understanding of TTI perceptions also hinder wider adoption (Pennanen et al., 2013, 2015). A study focusing on understanding the consumers' knowledge, interest and perceptions of TTIs involved 16 focus group discussions and a quantitative survey across Finland, Greece, France and Germany. It found that consumers in all these countries appreciated the idea of TTIs and understood their benefits, especially in warmer climates. However, the technologies did not fully meet consumer expectations. Concerns included aspects of TTI design (e.g., color choices), unclear interpretation instructions detached from the packaging, and doubts about accuracy—particularly because TTIs respond only to temperature, not directly to microbial activity (Pennanen et al., 2013). The general acceptance of the concept was positive, but practical implementation requires improvements in design, communication, and packaging integration. The study also emphasized the need for consumer education (Pennanen et al., 2013). Another survey among German businesses, including production, processing, logistics, wholesale, and retail reported similar findings across three supply chains: B2C for raw pork sausage, B2B for fish, B2C e-commerce for mixed goods. Product inspection is mainly static. TTIs are rarely adopted for dynamic temperature monitoring, and real-time data exchange among stakeholders is challenging (Waldhans et al., 2024).

Similar situations exist in QR code applications for shelf-life monitoring. Although a large amount of research has been conducted on QR codes in food information transmission (Li et al., 2024; Peleg & Saguy, 2024; Saguy & Cohen, 2024), several challenges hinder its widespread usage. Five main issues have been identified: (1) *Consumer engagement* – consumers show a low willingness to scan QR codes; (2) *High technical costs* – while printing and applying QR codes are inexpensive and relatively simple, requiring only a computer/code generator, QR code printer, and tags, the cost for building and maintaining a food traceability system or purchasing access to a commercial traceability platform is a significant barrier for food companies, in particular small and medium size companies; (3) *High marginal cost* – consumers need to take additional time to scan the QR codes using their smart devices and complete some complex actions, such as manually inputting a long traceability code on the platform linked to QR codes; (4) *Information overload* - After scanning the QR codes, consumers are often confronted with detailed and complex product information, which can be overwhelming and complicate decision-making about food; and (5) *Technical barriers* - Decoding of QR codes becomes challenging when QR codes are pasted on curved surfaces of food packaging, as these deformations may lead to pattern distortion and irregular module spacing (Li et al., 2024). Nevertheless, incentives such as coupons or rewards integrated into QR codes have been shown to improve user satisfaction and purchasing motivation, encouraging wider adoption by food companies (Li et al., 2024).

One critical issue relates to the cost of product returns for retailers. In the US alone, the total cost for consumer returns in 2023 was reported to reach $743 Billion (Sellercloud, 2024), although accurate data specific to perishable goods is lacking. Mishandling during transportation and/or inadequate storage conditions by consumers can increase the returns rate of food products, with significant cost implications. Additionally, a QR code or TTI that signals the end of shelf life after a product has been partially consumed could trigger false alarms and even severe anxiety. Given that consumer education is a long-term process, the unique value of TTIs must be clearly and consistently communicated. Achieving this will require collaboration among industry stakeholders, consumer organizations, and academic institutions to develop effective communication and outreach strategies.

## 6. Challenges and opportunities

### 6.1. Indicators and sensors for shelf-life monitoring

Existing TTIs and FIs technologies face several limitations, such as narrow sensing scope, lack of integration with location tracking, and environmental sustainability concerns. Most indicators detect only a single quality attribute after calibration. This narrow scope makes it difficult to capture the full historical condition of a food product. For example, a TTI may indicate that microbial growth remains within acceptable limits, yet the product could still lose consumer appeal due to changes in nutrition or sensory. A promising direction involves the development of multifunctional indicators capable of detecting multiple attributes related to quality, safety, and nutrition, along with providing an overall score. This can be achieved by combining multiple TTIs with different activation energies or by integrating both TTIs and FIs.

Current indicators also lack the ability to show when or where environmental changes (e.g., temperature abuse) occur during distribution. This absence of temporal and spatial resolution limits their effectiveness in pinpointing critical control failures and tracing quality or safety issues. Integrating tracking technologies, such as QR codes, could help address this issue by enabling periodic scans that record location and time-specific data. Another promising approach involves the use of Internet of Things (IoT) systems built on wireless sensor networks (Luo et al., 2022; Misra et al., 2020). These systems allow real-time monitoring by continuously collecting and transmitting data on key storage conditions, including temperature, humidity, and gas composition. Data transmission options vary by applications and include Wi-Fi (for warehouses), cellular networks (3G–5G, for transit), and satellite communications (for remote supply chains). However, data transmission reliablity and cost remain significant bottlenecks. Low-cost sensors are often constrained by limited battery life, low energy efficiency, and reduced accuracy. Additionally, network instability during transport can interrupt data flow and lead to data loss. Future solutions will require the development of low-power communication protocols, efficient data buffering, and edge computing strategies to ensure reliable operations throughout supply chains.

Environmental sustainability is another important consideration in the development of future sensing systems. Traditional indicators often rely on synthetic dyes and plastic substrates, which could raise significant environmental concerns. Recent research has focused on biodegradable alternatives, such as plant-based pH indicators (e.g., anthocyanins and curcumin) combined with compostable packaging films. These materials offer eco-friendly solutions; however, further studies are needed to evaluate and improve their performance, durability, and cost-effectiveness under real-world conditions.

### 6.2. Integration of tracking and monitoring technologies

Integrating tracking with monitoring technologies presents both opportunities and challenges. One major hurdle is the lack of standardized regulatory frameworks. Most existing regulations focus solely on food-contact safety (Ghaani, Cozzolino, Castelli, & Farris, 2016). In the European Union, Regulation (EC) No. 1935/2004 and Commission Regulation (EC) No. 450/2009 apply to intelligent packaging materials that come into contact with foods. In the United States, the FDA requires that indicator components in direct contact with food comply with food-contact material safety standards. However, there are no guidelines addressing integrated systems in terms of performance, accuracy, or predictive reliability. This regulatory gap creates uncertainty for manufacturers and slows industrial adoption. Establishing a robust evaluation framework and reducing cost barriers will be essential to support widespread commercialization.

Consumer interpretation remains a challenge. As previously

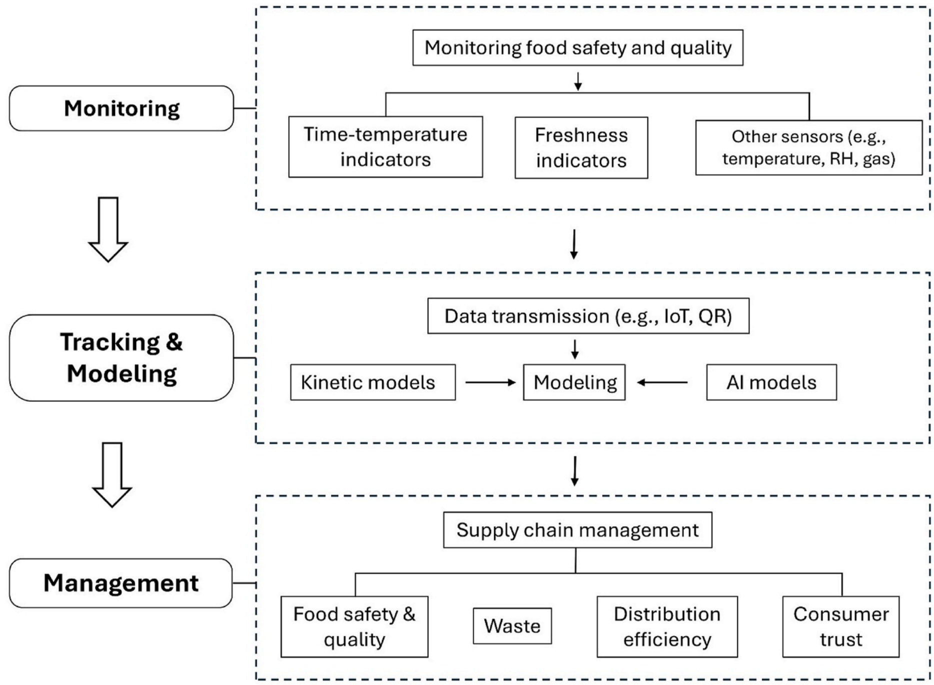


**Fig. 6.** Conceptual framework integrating monitoring, tracking, and modeling into dynamic supply chain management.

discussed, many consumers already misunderstand expiration date labels. Introducing color-changing labels or smart sensors may increase confusion if not carefully designed. Research is needed to understand how different user groups perceive and respond to such technologies. To ensure consumer trust, clear instructions, targeted educational outreach, and intuitive label design are essential. Smartphone integration may help simplify user interactions. QR-based indicators or sensors, when paired with mobile apps, can provide easy and intuirive access to information on shelf life and quality. However, variations in camera quality and lighting conditions can affect detection accuracy. Developing robust image-processing algorithms and user-friendly apps is therefore a top priority. Personalized expiration labeling also offers a promising opportunity. Indicators and sensors can estimate the remaining shelf life based on actual distribution and storage conditions. When connected to digital tracking platforms, these systems could support inventory optimization for retailers and help consumers make more informed purchasing and consumption decisions. Achieving this level of integration will require reliable sensing infrastructure, strong data privacy protection, and collaborations among manufacturers, distributors, and retailers.

### 6.3. AI modeling

AI and machine learning (ML) offer innovative approaches to predicting food shelf life (Kakani et al., 2020; Rashvand et al., 2025), moving beyond traditional kinetic models such as Arrhenius-based equations. While classical models remain useful, they rely on simplified assumptions that typically focus on a single quality attribute and often fall short under the complex and variable conditions of supply chains. In contrast, AI models can process multivariate data, including weather, packaging, transit delays, and historical spoilage patterns. This enables adaptive, multi-attribute prediction by leveraging advanced machine learning algorithms, ranging from ensemble methods like random forests to modern deep learning architectures. For instance, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) can extract meaningful patterns from complex sensor data. Sophisticated sequence modeling architectures such as Transformer and Long Short-Term Memory (LSTM) RNNs, originally developed for large language models (LLMS), are well-suited to capturing complex temporal dynamics. These models can significantly improve the ability to represent and predict dynamic behaviors of dynamic systems. Similary, core deep learning techniques, such as CNNs, are effective at modeling nonlinear interactions among multiple variables. When incorporating CNNs into kinetic modeling, it is possible to better capture multivariate dependencies and nonlinear effects that are often difficult to handle using traditional approaches.

AI also supports decision-making in supply chain management (Toorajipour et al., 2021). Reinforcement learning and optimization algorithms can be used to dynamically adjust transportation routes based on shelf-life predictions. Clustering and classification models can recommend alternative storage and transportation conditions by analyzing historical quality responses under different environments. Forecasting models, such as time-series neural networks and gradient boosting machines, can automate inventory and warehouse operations by predicting demand and spoilage risk. Additionally, pricing strategies can be guided by appropriate models or deep learning algorithms that link real-time product quality to market value and consumer behavior. These AI-driven tools can help reduce waste, improve safety, and enhance efficiency across food distribution networks.

Despite these benefits, several challenges remain. Most AI models require large, high-quality datasets for training, which may not be readily available across all supply chains. Data privacy and ownership, especially when consumer-level tracking is involved, may raise ethical and regulatory concerns. These challenges need to be addressed to ensure responsible and effective AI deployment.

### 6.4. Integrated framework and outlook

We present a conceptual framework that illustrates how monitoring, tracking, and AI-driven modeling can be integrated for the intelligent management of future food supply chains (Fig. 6). This framework consists of three interconnected main components: (1) Monitoring, where indicators or sensors monitor food quality and safety; (2) Tracking and modeling, where sensor data is collected and transmitted via networks, such as QR code scanning and IoT systems. These data streams support real-time AI predictive modeling to estimate remaining shelf life and detect potential safety risks; and (3) Management, where predictions inform supply chain management decisions aimed at enhancing food safety, reducing waste, improving distribution efficiency, and building consumer trust.

## 7. Conclusions and recommendations

TTIs and FIs are effective tools for shelf-life monitoring. When successful integrated with product tracking technologies, the hybrid systems can support traceability and real-time quality assessment. Recent innovations, such as QR-based freshness indicators, offer promising possibilities for more responsive, transparent, and efficient supply chain operations. However, several challenges remain. These include the need for accurate, environmentally friendly, and cost-effective sensors or indicators, reliable data communication, storage and interpretation, appropriate regulatory frameworks, and broad consumer acceptance. In parallel, robust AI models with reliable data tranining need to be developed to handle the real-world variability in food quality and supply chain conditions.

These challenges also present significant opportunities for unified, multidisciplinary collaboration. They create space for experts in sensing technologies, food safety, quality changing kinetics, QR integration, AI modeling, data communication, and consumer science to work together in developing, validating, and scaling practical applications. Stakeholders involvement is equally critical. For policymakers, establishing clear regulatory guidelines on labeling, shelf-life prediction, and digital data usage will support broader adoption. For technology developers, considerations such as cost-effectiveness, ease of implementation, and compatibility with existing logistics systems are essential. Strengthening collaboration across disciplines and sectors is key to building smarter and more resilient food supply chains.

While our discussion has focused primarily on food supply chains, the principles of rapid-response and real-time quality tracking are equally applicable to medical logistics, such as those involving blood transfusions and vaccines. Similar QR- or IoT-based sensing platforms (see Fig. 6) could be adopted in this context. However, the indicators or sensors must be specifically developed and rigorously validated to meet the stringent regulatory requirements unique to medical applications.

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### Data availability

No data was used for the research described in the article.

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