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Assessment of intelligent packaging systems to improve resource efficiency along the supply chain of fresh produce

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Meiner Familie

Die Voraussetzung für Wissen ist die Neugier.

Jacques-Yves Cousteau (1910–1997), französischer Meeresforscher

Abstract

Assessment of intelligent packaging systems to improve resource efficiency along the supply chain of fresh produce

The aim of this thesis was the assessment of intelligent packaging systems along different supply chains of fresh produce and their contribution to improve resource efficiency. As part of the work, a novel method was used for the read-out of intelligent packaging systems, in particular time–temperature–indicators (TTI), for testing and evaluation. First, an app-based system for the color read-out of TTIs was developed and investigated considering various technical and environmental parameters under laboratory conditions. By means of a survey of different food chain stakeholders, the status quo regarding the use of temperature monitoring systems including intelligent systems and data management systems was gathered. In pilot studies, the application of the app-based TTI-read-out system for both temperature monitoring along different supply chains (Business-to-Business and Business-to-Consumer) and shelf life prediction of raw pork sausage and ready-to-eat salad was validated. The results revealed that reading out TTI discoloration and developing a TTI shelf life model are generally possible using the newly developed app. After calculating corrected color values under the consideration of different influencing parameters, the results of TTI read-outs were comparable to that of a conventional colorimeter. Pilot studies revealed that the newly developed app-based read-out system is generally able to monitor temperature conditions along different supply chains and to indicate temperature variations. In the shelf life studies, the system is also found suitable to generally reflect spoilage kinetics of selected products adequately by the discoloration kinetics based on app measurements. The comparison of measured and predicted color values revealed a high accordance. However, under practical conditions, environmental influences in real supply chains affect the temperature monitoring and shelf life prediction by the app, and further optimizations are necessary. The study results serve as proof of concept for the app-based application of intelligent packaging systems. Although the survey revealed that the use of intelligent systems is still not widespread, the developed system is a suitable tool for continuous temperature monitoring and product-accompanying control for the simple determination of the shelf life throughout the supply chain. By providing further information, they have a high potential to save valuable resources along the food supply chain.

Kurzfassung

Bewertung intelligenter Verpackungssysteme zur Verbesserung der Ressourceneffizienz entlang der Lieferkette von Frischprodukten

Ziel der Arbeit war die Bewertung intelligenter Verpackungssysteme entlang unterschiedlicher Lieferketten von Frischprodukten sowie deren Beitrag zur Verbesserung der Ressourceneffizienz. Im Rahmen der Arbeit wurde eine neuartige Methode zur Auslesung intelligenter Verpackungssysteme, im Speziellen von Zeit-Temperatur-Indikatoren (TTI), getestet und bewertet. Zunächst wurde ein App-basiertes System zur Farbauslesung von TTIs unter Berücksichtigung verschiedener technischer und umgebungsbedingter Parameter in Laborumgebung entwickelt und untersucht. Mittels einer Umfrage verschiedener Akteure der Lebensmittelkette wurde der Status Quo zur Nutzung von Systemen der Temperaturüberwachung, inklusive intelligenter Systeme, und des Datenmanagements erfasst. In Pilotstudien wurde sowohl die Anwendung des App-basierten TTI-Auslesesystems für das Temperaturmonitoring entlang verschiedener Lieferketten (Business-to-Business und Business-to-Consumer) als auch zur Haltbarkeitsvorhersage roher Schweinebratwurst und Ready-to-Eat Salat validiert. Die Ergebnisse zeigten, dass das Auslesen der TTI-Entfärbung und die Erstellung eines TTI-Haltbarkeitsmodells mittels der neu entwickelten App generell möglich sind. Nach Kalkulation korrigierter Farbwerte unter Berücksichtigung verschiedener Einflussparameter zeigte die Auslesung der TTIs vergleichbare Ergebnisse mit einem konventionellen Farbmessgerät. Die Pilotstudien zeigten, dass das neu entwickelte App-basierte Auslesesystems generell Temperaturbedingungen entlang unterschiedlicher Lieferketten überwachen und Temperaturschwankungen anzeigen kann. Aus den Haltbarkeitsstudien ging hervor, dass das System zudem geeignet ist, Verderbskinetiken der ausgewählten Produkte durch die Entfärbekinetiken basierend auf den App-Messungen grundsätzlich adäquat widerzuspiegeln. Der Vergleich gemessener und vorhergesagter Farbwerte zeigte eine hohe Übereinstimmung. Jedoch zeigte sich unter praktischen Bedingungen, dass Umwelteinflüsse in realen Lieferketten das Temperaturmonitoring und die Haltbarkeitsvorhersage per App beeinflussen und weitere Optimierungen notwendig sind. Die Ergebnisse der Studien dienen als Machbarkeitsnachweis der App-basierten Anwendung intelligenter Verpackungssysteme. Auch wenn die Umfrage zeigte, dass die Nutzung intelligenter Systeme noch wenig verbreitet ist, ist das entwickelte System ein geeignetes Werkzeug für eine kontinuierliche Temperaturüberwachung und für eine produktbegleitende Kontrolle zur einfachen Bestimmung von Haltbarkeitszeiten entlang der Lieferkette. Durch die zusätzlichen Informationen bieten sie ein hohes Potential, wertvolle Ressourcen entlang der Lebensmittellieferketten einzusparen.

Contents

1 Introduction

1.1 Food and resource waste in supply chains of perishable products

The protection and maintenance of a sustainable development are nowadays one of the key challenges on a global level. To overcome these challenges, the United Nations General Assembly published the “2030 Agenda for Sustainable Development”, addressing political targets to all countries, economic and scientific stakeholders, and individual persons and defining 17 Sustainable Development Goals (United Nations General Assembly, 2015). Goal 12 aims to achieve an overall sustainable consumption and production, containing among others the efficient use of natural resources, waste reduction, and effective information management. One of the main targets is 12.3, reduced food losses along the supply chain and 50 % decrease per capita of food waste at retailers and consumers by 2030 (Caldeira et al., 2019; United Nations General Assembly, 2015). The Food and Agriculture Organization (FAO) of the United Nations (UN) indicated that food loss is the amount of food discarded at all steps of the supply chain except at retailers, food services, and final consumers (FAO, 2019). Food waste is the amount occurring at the stage of retailers, food services, and final consumers. The definition mainly focused on the supply chain steps, excluding the discard of inedible parts and parts used for other valuable purposes, such as feed or industrial use (FAO, 2019; Gustavsson et al., 2011). To fulfill SDG 12.3 on the EU level, the new circular economy action plan and the Farm to Fork strategy as part of the European Green Deal require member states to take measures for the prevention and reduction of food loss and waste (FLW) on every step of the supply chain (Caldeira et al., 2021; European Commission, 2020a, 2020b). The Directive 2018/851 indicated that the UN targets should be implemented by a stepwise reduction of the waste amount of 30 % until 2025 and 50 % until 2030 (European Parliament and the Council, 2018). In Germany, reduced food waste is part of the national “Sustainable Development Strategy” (German Federal Government, 2021). The “National Strategy for Food Waste Reduction” by the Federal Ministry for Food and Agriculture also aims to reduce the amount of food waste at the consumer and retail level by 50 % and a general minimization along the supply chain (Federal Ministry of Food and Agriculture, 2019).

To reduce FLW, high research effort was made to determine its amount along the entire supply chain. The exact calculation of FLW in different countries and sectors is challenging due to variations concerning methodology, data collection, and modeling

(Caldeira et al., 2019). In 2011, comprehensive studies of the FAO estimated for the first time the worldwide amount of FLW as one third of the food from production to final consumption (Gustavsson et al., 2011). The recent Food Waste Index report 2024, published by the United Nations Environment Programme (UNEP), reported approximately 1.05 billion tons of global food waste per year in the sections of retails, food services, and households (UNEP, 2024). FLW in Europe is calculated as 129 megatons (Mt) per year, with approximately half emerging at the consumer stage (Caldeira et al., 2019). In Germany, a total FLW amount of 11 Mt was reported by the Federal Statistical Office for 2020, with nearly 60 % caused by the final consumer (Destatis, 2022; Schmidt et al., 2019). Considering individual food groups, mainly sensitive and perishable products contribute to the FLW amount. Cereal products, fruits, and vegetables belong to both worldwide as well as European and German levels to the highest share of FLW (Flanagan et al., 2019; Gustavsson et al., 2011; Herzberg et al., 2020). However, the FLW in the group of animal-based products, in particular the meat and meat product supply chain, must be considered. According to Benning et al. (2021), approximately 12 % of the produced meat worldwide gets wasted from slaughtering to retail. European studies reported that 23 % of FLW in the meat sector from the primary production to consumption, indicating that more than a half is caused by the consumer (Karwowska et al., 2021). This is precisely important, because FLW is inevitably associated with the wasted number of environmental resources such as water, energy, and cropland capacities used for the production and supply (Kummu et al., 2012; Rossaint & Kreyenschmidt, 2015).

Food supply chains are highly resource intense due to animal husbandry, crop cultivation, processing steps, and complex transport routes. Greenhouse gas emissions (GHG) occurring on the steps of packaging, transport, retail, and household consumption are globally estimated as 3.6–4.8 gigatons (Gt) carbon dioxide equivalent (CO2-eq) (Crippa et al., 2021; Tubiello, Flammini, et al., 2021; Tubiello, Rosenzweig, et al., 2021). Moreover, 1.0–1.6 Gt CO2-eq. are released during the waste disposal stage (Crippa et al., 2021; Tubiello, Flammini, et al., 2021; Tubiello, Rosenzweig, et al., 2021). As for the GHG generated throughout the supply chain, the carbon footprint of FLW increases later in the chain the waste occurs (FAO, 2019). FLW in the meat supply chain shows greater consequences in environmental impact (Bilska, Tomaszewska, Kołożyn-Krajewska, et al., 2020; FAO, 2013; Gustavsson et al., 2011). The total anthropogenic GHG emissions are considerably caused by livestock farming during breeding and meat production (Benning et al., 2021; FAO, 2016, 2021; Gerber, 2013; IPCC, 2019; Rossaint & Kreyenschmidt, 2015; Tubiello, 2019), especially the beef and pork meat production (Vries & Boer, 2010; Weiss & Leip, 2012).

The FLW are caused by wide-ranging factors due to the high complexity of food supply chains with various steps, products, and requirements. In developing countries, FLW occurs especially at the post-harvesting and processing steps due to limited technological developments, lacks in transport, storage, and infrastructure, often combined with hot climate conditions (FAO, 2019; Joardder & Hasan Masud, 2019; Papargyropoulou et al., 2014; Parfitt et al., 2010). In industrialized countries, FLW causes are quite difficult because supply chains are further technologically developed. FLW occurs mainly at the later supply chain stages. Along food cold chains, the primary reasons for food waste are interruptions and lacks in adequate temperature conditions. The food cold chain is usually a multi-step process: pre-cooling of goods; cooled transports and storages; transshipment and platform points; depots as well as the wholesale, retail, transport, and consumer storage (Amath et al., 2021; Mack et al., 2014; Raab et al., 2008), offering the opportunities for temperature fluctuations and interruptions. The early detection of incorrect temperature conditions should be timely and therefore reduce the amount of food waste. This finding also requires good information management between stakeholders (Ndraha et al., 2020).

Another important reason for FLW is that food products are discarded due to the expiry of their best-before-dates (BBD). This is particularly applied to fresh produce and products with very short shelf lives (Kreyenschmidt, 2012; Moraes et al., 2020). The main reason for food waste at the retailer is, besides external defects as color changes or damages, the expiry of the labeled shelf life (Karwowska et al., 2021; Lebersorger & Schneider, 2014), especially many consumers rely on the BBD as the main criterion for rejection of the product or misinterpret different shelf life labels (Gunders, 2012; Neff et al., 2019; Samotyja & Sielicka-Różyńska, 2021; Toma et al., 2020). Moreover, in the food service industry, an incorrect storage handling and exceeded expiry dates are identified as food waste causes (Bilska, Tomaszewska, & Kołożyn-Krajewska, 2020; Christ & Burritt, 2017). However, the shelf lives of properly handled and stored food products under adequate temperature conditions are often longer, and they are still in high quality and safe condition. Waste reduction can be achieved by adjusting the standard shelf life of the products, retaining the food safety. Therefore, shelf life knowledge as well as quality and spoilage characteristics is of great importance.

1.2 Influence on shelf life of perishable products and shelf life modeling

The quality and shelf life of food products, especially fresh produce, are complex and caused by multiple and product specific intrinsic and extrinsic factors affecting spoilage processes. Animal-based products are known for their rapid microbial spoilage characteristics, causing short shelf lives. The shelf life of perishable products such as meat is – besides lipid oxidation and enzyme activity – mainly determined by microbial growth and proliferation of specific spoilage organisms (SSO) such as lactic acid bacteria, *Pseudomonas* spp. or *Brochothrix thermospacta*, resulting in color, odor, and flavor changes (Bruckner et al., 2012; Koutsoumanis & Taoukis, 2005; Kreyenschmidt, 2012; Kreyenschmidt & Ibald, 2012; Nychas et al., 1998). The spoilage of plant-based products is mainly affected by respiration processes, water loss, and ripening (Krämer & Prange, 2017; Lamberty & Kreyenschmidt, 2022; Robertson, 2010), resulting in sensory changes. However, their shelf lives can also be highly determined by microbial spoilage (Lianou et al., 2016), especially fresh-cut products and ready-to-eat meals. Microbial spoilage makes food inedible, unsafe, and non-recoverable (Kantor et al., 1997) and leads to consumer rejections and economic losses (Koutsoumanis & Taoukis, 2005; Nychas et al., 2008). To properly evaluate the shelf life of fresh produce, knowledge about the different influencing factors on quality and the actual, real-time status of quality and the remaining shelf life should be intensified. Temperature is one of the most important influencing factors on the spoilage processes of perishable food and therefore on the quality and shelf life (Kreyenschmidt & Ibald, 2012). Temperature abuse along food supply chains has a high impact on product quality and safety (Bruckner, 2010; Ndraha et al., 2018). Shelf lives of perishable fresh produce can highly vary depending on temperature conditions along the chain, combined with the initial microbial load of the products and influence of other factors. Therefore, monitoring the temperature along the cold chain is highly important (Taoukis et al., 2016) to achieve a good estimation of the associated quality and shelf life of a food product.

For an accurate shelf life estimation, predictive microbiology can be used by calculating microbial growth based on mathematical models depending on different factors and factor combinations. For several years, particularly with substantial computer technology innovations, predictive microbiology plays a key role in evaluating food microbiology processes and safety issues (Whiting, 1995). Buchanan (1993) defined the classification of primary, secondary, and tertiary models. Primary models are used to describe the microbial growth or direct and indirect responses (e.g., growth of metabolic, absorbance) over a certain period, characterized by sigmoidal mathematical relationships (Buchanan, 1993; Whiting, 1995). Knowledge regarding the SSO and its spoilage activities in individual food products – also dependent on their packaging – is critically essential for an accurate shelf life prediction (Dalgaard, 1995; Koutsoumanis & Nychas, 2000). Examples for primary models are the Gompertz, most typically used to describe microbial growth, as well as the Logistic and Baranyi models (Gibson et al., 1987; Whiting, 1995). Secondary models are used to describe the dependency of primary model parameters on environmental conditions, e.g., temperature-dependent microbial growth (Whiting, 1995). Tertiary models combine primary and secondary models as a tool to calculate dynamic scenarios at fluctuating temperatures, commonly integrated in software applications (McDonald & Sun, 1999; Whiting, 1995). Predictive microbiology and a continuous temperature control support the Least Shelf Life First Out (LSFO) and First Expired First Out (FEFO) principles for an optimized cold chain management (Bruckner et al., 2013; Jedermann, Nicometo, et al., 2017). It is also a useful tool for the risk assessment in food chains and growth estimation of pathogenic bacteria (Augustin, 2011). Although classic microbiological methods are still required to analyze the quality and safety of food products, predictive shelf life models provide reliable information about the microbial status. Their importance has increased, precisely because of the efforts made to substitute short and static labeling with dynamic shelf lives. Dynamic shelf life modeling offers the possibility to more flexibly react in the short marketing windows of perishable products. The dynamic state of shelf life dates is a promising tool to avoid food waste of products that are still in a good condition (Poyatos-Racionero et al., 2018). The study of Albrecht et al. (2021) shows the successful application of a dynamic shelf life model based on microbial and sensory data in a pork meat supply chain. Moreover, in the political debate around FLW, proposals for the implementation of dynamic labels are increasing (Toma et al., 2020). A continuous information flow along food systems is given through the combination of supply chain-specific food (e.g., temperature data, microbial growth) and business data, predictive shelf life models, and thus can function as a decision support system (Yam et al., 2005).

However, the application of dynamic shelf lives based on predictive modeling is limited, as continuous and real-time monitoring of temperature data across the whole cold supply chain and a suitable infrastructure are not yet fully available (Corradini, 2018; Lamberty & Kreyenschmidt, 2022). Moreover, a highly accurate temperature measurement must be made to maintain a reliable shelf life modeling. Systems have already been described as part of Internet-of-things (IoT) technologies. The radiofrequency identification tag (RFID) and Wireless Sensor Network (WSN) applications for data acquisition and temperature monitoring along supply chains are known for years. Mack et al. (2014) studied continuous temperature monitoring across the supply chain of lamb meat using WSN technology. The use of RFID tags and ZigBee-based WSN to monitor food storage is described by Badia-Melis et al. (2015), Urbano et al. (2020), and Dinesh Kumar et al. (2022). The use of Long-Range Wide Area Network (LoRaWAN) technologies was also tested for a continuous temperature control along food supply chains (Jedermann et al., 2018).

However, these developments are still limited in their application along specific food chains. Electronic sensors are generally more expensive and therefore not suitable for the use on single packaging units. Temperature monitoring at the individual packaging level can be particularly important for shelf life modeling of fresh produce, such as perishable meat products, as temperature variations dependent on pallet levels also become visible (Jedermann, Praeger, & Lang, 2017; Raab et al., 2008). Furthermore, temperature monitoring by such technologies up to the final consumer is difficult due to issues on the range of data transmission and interconnection, sensor reutilization, and additional packaging costs (Urbano et al., 2020). Additionally, the end consumer cannot access the temperature data and thus has no insights into possible cold chain interruptions and remaining shelf life. To combine temperature monitoring and shelf life prediction, leading to good knowledge about remaining shelf lives of food products, and thus to a more efficient supply chain, other innovative and cost-effective solutions should be considered. Therefore, intelligent packaging systems are increasingly discussed with regard to a more sustainable food chain and food waste reduction (Jedermann, Nicometo, et al., 2017; Rossaint & Kreyenschmidt, 2015).

1.3 Intelligent packaging systems as a tool to reduce food waste

Intelligent packaging materials are defined as materials that “monitor the condition of packaged food or the environment surrounding the food”, which should not change any food composition or sensory characteristics or mislead the consumer of the given information, regulated by Regulation (EC) No 1935/2004 (The European Parliament and the Council, 2004) and the Commission Regulation (EC) No 450/2009 (The Commission of the European Communities, 2009). They can provide advantageous properties for actors along the food supply chain for the detection, tracing, and communication of products specific and environmental conditions (Restuccia et al., 2010; Yam, 2012) and, thus, support information management and decision-making processes as well as increase quality, safety, and shelf life of perishable products (Yam et al., 2005). Intelligent packaging solutions are already part of research and development for several decades (Taoukis & Labuza, 1989; Wells et al., 1987). First developments and patents were reported in the 1970s (Restuccia et al., 2010; Taoukis & Labuza, 1989), especially in Japan, North America, and Australia (Ghaani et al., 2016). Recently, intelligent packaging is rapidly and increasingly relevant due to the increased demand for product quality and safety and additional supply chain information, especially on the consumer side (Ahvenainen, 2003; Fuertes et al., 2016; Ghaani et al., 2016; Müller & Schmid, 2019). The sustainability in food supply chains as a promising basis for the increasing market development is increasingly debatable. Current studies on packaging trends and growth reported that a global market value for active and intelligent packaging was valued at $18.84 billion in 2021 with an estimated Compound Annual Growth Rate (CAGR) of 6.64 % by 2027 (Mordor Intelligence, 2023a). The COVID-19 pandemic in 2020 revealed the need for advanced packaging solutions to maintain safe and traceable food supply chains, especially for perishable products (Mordor Intelligence, 2023a, 2023b).

Multiple existing intelligent systems can be subdivided based on their technique: data carriers, such as RFID for supporting transport, storage and traceability in the chain, sensors for the detection of specific food analytes, and indicators that give information about temperature and product quality (Ahmed et al., 2018; Ghaani et al., 2016; Kerry et al., 2006; Kuswandi & Jumina, 2020; Yam et al., 2005). Sensors can detect the presence of specific chemical or biological food analytes in packaging, such as volatile compounds and pH (chemical sensors), biochemical reactions (biosensors), and gas concentrations (gas sensors) (Kerry et al., 2006; Kuswandi & Jumina, 2020; Vanderroost et al., 2014). Indicator systems provide information about the presence or absence of specific substances or their extent of reaction with each other, directly indicating by a visual change. They can be further subdivided into different categories. One classification is described by (Realini & Marcos, 2014): freshness indicators, integrity indicators, pathogen indicators, and time-temperature-indicators (TTI). TTIs are the most common indicators. They are simple temperature sensitive labels, demonstrating a color change based on their full or partial temperature history when attached to a food product (Taoukis & Labuza, 1989). The function principle is based on time- and temperature-dependent (electro)chemical, mechanical, enzymatic, or microbiological reactions, resulting in an irreversible color response (Kerry et al., 2006; Smolander et al., 2004; Taoukis & Labuza, 2003). TTIs can monitor the actual product status and, thus, can function as a temperature and product control along the food supply chain. When spoilage processes are known, they can be combined with mathematical models for the shelf life prediction of specific food products (Raab et al., 2008; Taoukis & Labuza, 1989; Wells et al., 1987). Several studies have monitored conventional supply chains of fresh produce using TTIs for shelf life prediction (Albrecht et al., 2020; Brizio & Prentice, 2014; Ellouze & Augustin, 2010; Taoukis, 1999). Therefore, it is important to know the temperature dependency of the spoilage kinetics and TTI kinetics, which can be expressed as the activation energy (E_a) (Taoukis, 2001). Additional information can be used for optimized decision making in logistic processes along the supply chain. Depending on the purpose of use, they can be applied to single packaging units or containers (Fang et al., 2017; Ghaani et al., 2016).

Numerous developments of TTI solutions were made in research. Gao et al. (2020) reported that 119 review and research papers studying different TTI systems were published from 2009 to 2019. Table 1.1 provides an overview about different TTI systems that are available on the market or part of research, including their principle and functionality, adjustment to products concerning their temperature ranges, activation methodology, analysis method, activation energy, application for specific products and supply chains, as well as the costs. Approximately all TTIs are suitable for the use along the whole supply chain of B2B and B2C, including distribution and consumer levels. The remarkable benefit of TTIs in comparison to data logger or RFID systems is their cost-effectiveness and simple handling (Taoukis & Labuza, 1989; Yam et al., 2005). The labels can be measured with electronic devices as colorimeters or scanners, as TTI systems based on a color response are the most widely used (Gao et al., 2020; Mohebi & Marquez, 2015). For stakeholders, a simple tool for temperature monitoring and remaining shelf life during storage is helpful for an optimized organization of sales and prevention of product rejections either due to temperature interruptions or the reaching of the expiry date. The redistribution of products, which must be sold out soon due to their best-before date, is an efficient way to prevent food waste and save spent resources (Bilska, Tomaszewska, Kołożyn-Krajewska, et al., 2020). However, although the global market is increasing and multiple systems are applicable for a wide range of product and temperature requirements, only a few systems were commercialized (Taoukis & Tsironi, 2016). There are several reasons for the lack of implementation in food supply chains. One is that specific requirements of different supply chain structures, such as Business-to-Customer (B2C) and

Business-to-Business (B2B) as well as the food e-commerce, are not intensely considered yet. These, however, are hurdles for a comprehensive use of intelligent packaging, as food supply chains and distributed products are characterized by high complexity and variety (Soltani Firouz et al., 2021). Furthermore, specific legal regulations regarding the use of TTIs in the food supply chain are missing (Ghaani et al., 2016; Soltani Firouz et al., 2021), and the responsibilities of the stakeholders concerning food safety are not clearly defined yet.

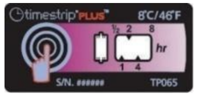
Another reason is that the information provided by TTIs is currently not integrated into traceability systems or data interfaces of food companies, which is however needed to use the information along the chain. The TTI read-out is mostly operated by specific color measurement devices. Albrecht et al. (2020) had reported that the integration of TTI data gathered using a colorimeter into software systems is generally possible. However, specific measurement devices are often elaborate in use, cost-intensive, and specialized for use in laboratories. Stakeholders along the chain require a user-friendly monitoring tool that can be easily integrated in existing and established workflows. Moreover, consumers, not using specific devices, can only evaluate the visual response of the TTI, resulting in misinterpretation or uncertainty in handling. A simplified handling and data integration is needed to digitally save and share valuable information about the temperature history and shelf life of related products along the supply chain. The use of smartphone tools for digital read-out and general information supply can overcome these challenges (Albrecht et al., 2020; Fang et al., 2017; Poyatos-Racionero et al., 2018). Modern smartphone devices and app technologies offer a wide range of possibilities for the development of cameras and app-based color detection systems. Furthermore, smartphones can be used for the data transfer into cloud-based systems. Then, an integration into existing standards, as the Electronic Product Code Information Services (EPCIS), would be possible to store temperature and supply chain information for traceability (Thakur & Forås, 2015), which would then correspond to an IoT technology. Data sharing and communication structures between different supply chain actors can improve product quality, safety, logistic processes, and the entire interorganizational infrastructure and transparency as well as the final consumer's confidence (Anica-Popa, 2012; Eden et al., 2011; Hertog et al., 2004; Hsiao & Chang, 2017; Mercier et al., 2017).

Even if modern smartphones and their camera features are generally suitable for the read-out of TTIs, only few approaches are available for certain labels concerning the analysis by smartphone. The use of such digital solutions by stakeholders is missing and widely unknown, which consequently also hinders the successful implementation of TTI systems. Studies investigating the technical requirements of digital read-out systems for TTIs using smartphone and the examination evaluation of these systems when applied in real food supply chains for perishable products are lacking.

Table 1.1. Overview of commercially available TTI systems

TTI System	Image	Principle and functionality	Adjustment to products	Activation	Analysis	E_a [kcal/ mol]	Application	Price	References
3M™ Monitor Mark™ (3M Company, St. Paul, MN, USA)	 (Mohebi & Marquez, 2015)	Diffusion-based: Blue-dyed fatty ester with specific melting point diffusing along a porous blotting paper, resulting in an irreversible color change depending on specific temperature threshold/melting point of the ester	Type and concentration of the ester can be adapted to temperature ranges (-15°C–26°C) and shelf lives (2 d, 7 d, 14 d)	Manual combining viscoelastic ester tape with blotting paper by removing an activation strip	Visual color analysis: Diffusion distance from initial point shows minimum estimated time above threshold temperature; comparison with response cards; no electronic device known	9.8	Broiler chicken, meat, drugs, vaccines, medical diagnostic kits, blood substances	≤ € 1.95 per label	(3M, 2006, 2022; Hogan & Kerry, 2008; Kerry et al., 2006; Mohebi & Marquez, 2015; Realini & Marcos, 2014; Smolander et al., 2004; Taoukis & Labuza, 1989)
CoolVu™ (Evigence Sensors, Yokne'am, Israel; former Freshpoint)	 (Kuswandi & (Jumina, 2020)	Dissolution-based: Reaction of a transparent etchant layer with an aluminum layer resulting in a time and temperature dependent discoloration from silver to white	Thickness of the aluminum layer or concentration of the glue can be adjusted to product shelf lives	Two head applicator on the packaging line to combine etchant layer with aluminum layer	Visual color analysis	N/A	Products with short and long shelf lives, pharmaceuticals, vaccines, cosmetics, baked goods, beverages	N/A	(Kalpana et al., 2019; Kuswandi & Jumina, 2020; Taoukis & Tsironi, 2016; Vanderroost et al., 2014)

TTI System	Image	Principle and functionality	Adjustment to products	Activation	Analysis	E_a [kcal/ mol]	Application	Price	References
Smartdot (Evigence Sensors, Yokne'am, Israel, former Freshpoint)	 (Own figure, 2022)	Same principle as CoolVu™; color change from green to red due to dyed layers	Same principle as CoolVu™	Desktop dispenser	Visual color analysis, analysis with colorimeter or smartphone	N/A	Bakery and frozen products	N/A	(Evigence, 2022; Kalpana et al., 2019)
Fresh-Check (Temptime Corporation®, Morris Plains, New Jersey, part of Zebra Technologies Corp.)	 (Zebra Technologies Corp., 2020)	Polymer-based: Temperature-dependent, irreversible 1,4 addition polymerization of diacetylene monomers to a dark colored polymer, UV filter for light protection	Calibration of the reactant based on the specific temperature range	Self-activating; mandatory storage at low temperatures before use	Visual color analysis by comparison to a reference color circle with a "use-by"-limit or measurement by a laser optic wand scanner	19.9	Fresh food, e.g., chicken, meat, fish; pharmaceuticals, vaccines	$ 0.25–0.35 per package	(Fortin & Goodwin, 2008; Hogan & Kerry, 2008; Huffman et al., 2017; Kerry et al., 2006; Mohebi & Marquez, 2015; Nuin et al., 2008; Smolander et al., 2004; Taoukis, 1999; Zebra Technologies Corp., 2020)
OnVu™ (Bizerba SE & Co. KG, Balingen, Germany)	 (Bizerba, 2020)	Photochromic-based: Time- and temperature-dependent discoloration from blue to colorless of a UV sensitive ink containing benzopyridine pigments	Adjustable to specific shelf lives through different AE of UV light charging	Specific chargers; Activation of ink by UV light; irreversible discoloration through a UV filter	Visual color analysis or by colorimeter	23.2–25.3	Fresh food, e.g., meat, chicken, fish, seafood, dairy products	Few cents per label	(Brizio & Prentice, 2014; Haarer & Levy, 2006; Hogan & Kerry, 2008; Kalpana et al., 2019; Kreyenschmidt et al., 2010; Mai et al., 2011; Mohebi & Marquez, 2015; Realini & Marcos, 2014; Tsironi et al., 2016)

TTI System	Image	Principle and functionality	Adjustment to products	Activation	Analysis	E_a [kcal/mol]	Application	Price	References
Timestrip® PLUS / Timestrip® FOOD (Timestrip UK Ltd., Cambridge, UK)	 (Sigma-Aldrich, 2023)	Irreversible coloration through a blue liquid dye moving through a membrane when threshold temperature is exceeded; coloration stops when temperature is below the threshold (liquid gets solid); indication of total time of temperature exceedance	indicators for temperature ranges from -20°C–38°C (specific Food Indicators from 3°C–10°C); each indicator is provided with a unique serial number	At room temperature (> threshold) by manual or automatic (Production Line Feeder) squeezing a blister on the indicator; activation line “On” appears	Visual indication of the time above threshold temperature	N/A	Frozen and chilled products, e.g., seafood; pharmaceuticals, vaccines, cosmetics blood, chemicals	€ 1.7–2.6	(Ghaani et al., 2016; Realini & Marcos, 2014; Sigma-Aldrich, 2023; Timestrip, 2022a, 2022b)
Tempix-Smart Label (Tempix AB, Järvsö, Sweden)	 (Kuswandi & Jumina, 2020)	Barcode-based: Application of a standard barcode label including a cover label with an activator liquid forming a barcode control bar; Discoloration of the control bar when exposed to temperature above the correct range	Adjustable to different temperature requirements (-35°C–32°C)	By thermal label printer with cover label applicator to encapsulate the liquid, cold chain monitoring starts after activation, triggering time is adjustable by software	Conventional barcode scanner	N/A	Temperature sensitive food, pharmaceuticals, cosmetics, wine, fish, salad, ice, meat, blood	≤ $ 0.01 per label	(Ghaani et al., 2016; Kuswandi & Jumina, 2020; Tempix AB, 2019; Tichoniuk et al., 2021)

TTI System	Image	Principle and functionality	Adjustment to products	Activation	Analysis	E_a [kcal/ mol]	Application	Price	References
TOPCRYO (CRYOLOG, Nantes, France)	 (Cryolog, 2022)	Microbial-based: Coloration from green to red based on the reaction of *Carnobacterium maltaromaticum* and color changing indicator (fuchsin) in a nutritive medium, all included in a multilayer plastic sachet	Adjustable to temperature ranges of 2°C–12°C, 12 h up to 12 d	Activated as soon as they are attached to a temperature-sensitive product	Visual color analysis, additional recording of real-time data by QualiBooR system: barcode reader at selected steps of the chain for traceability propose	N/A	Temperature sensitive packed/ perishable foods, meat	Few cents	(Cryolog, 2022; EFSA, 2013; Hogan & Kerry, 2008; Kalpana et al., 2019; Mohebi & Marquez, 2015; Realini & Marcos, 2014)
Freshtag™/ Checkpoint® (Vitsab™ International AB, Limhamn, Sweden)	 (Own figure, 2022)	Enzymatic-based: pH decrease induced color change from green to orange/red based on the hydrolysis of a lipid substrate with a pH indicator in a lipolytic enzyme solution	Varying Enzyme-substrate concentrations can be adapted to temperature ranges and response life	Manual or on-line automatic break of a seal to combine substrate and enzyme solutions	Visual analysis by comparing to a five-point color scale or by spectrophotometer (measurement of a*-value)	16.4–24.4	Poultry, ground beef, (frozen) fish and seafood, dairy products, frozen vegetables, mushrooms	$ 0.10	(Biji et al., 2015; Bobelyn et al., 2006; Chun et al., 2013; Fang et al., 2017; Giannakourou et al., 2005; Giannakourou & Taoukis, 2003; Han et al., 2018; Hogan & Kerry, 2008; Kalpana et al., 2019; Kerry et al., 2006; Realini & Marcos, 2014; Smolander et al., 2004; Taoukis, 1999; Tsironi et al., 2016; Tsironi et al., 2017)

TTI System	**Image**	**Principle and functionality**	**Adjustment to products**	**Activation**	**Analysis**	**E_a [kcal/ mol]**	**Application**	**Price**	**References**
Smart Tag™/ Freshcode (Varcode LTD, Chicago, IL, USA)	 (Varcode, 2022)	Barcode-based: Multilayered dynamic barcode, which changes time and temperature dependent by an appearing ink dependent on the predetermined melting point, specific change shows time passing over specific threshold temperature	Configurations from -20°C–40°C, specific time and temperature threshold adjustable, adjustable to various types of barcodes (e.g. 128, GS1 or EAN)	Pulling of the start tab	Handheld or fixed barcode scanner or smartphone app for barcode scanning and data collection into a cloud-based management system	N/A	Meat, poultry, seafood, dairy, wine, e-commerce, pharmaceuticals	N/A	(Biji et al., 2015; Packaging Journal, 2019; Realini & Marcos, 2014)

N/A: Data not available

1.4 Research questions and outline of the thesis

The main objective of this thesis is to assess intelligent packaging systems as a tool for temperature monitoring and shelf life prediction of perishable food products to improve the resource efficiency along the supply chain of fresh produce. The focus is on the development and investigation of an app-based tool for the read-out of TTIs along the transport and storage of selected products to optimize logistic processes and storage at the consumer to reduce food waste.

For this purpose, the following research questions are formulated:

- Is it possible to digitally read out TTIs using a smartphone application, considering specific environmental and technical requirements? (chapter 2)
- How is the status quo regarding the use of temperature monitoring and data management systems in food supply chains, also concerning intelligent monitoring tools? (chapter 3)
- Are app-based TTI systems adaptable as a temperature monitoring tool and for the indication of weak points along different B2C and B2B food supply chains? (chapter 3)
- Can app-based TTI systems be used for the shelf life prediction of animal- and plant-based products based on spoilage and quality characteristics to optimize supply chain procedures and consumer storage and to reduce food waste? (chapter 4, 5)

The first part of the thesis (chapter 2) focuses on the development and evaluation of a smartphone app for the digital read-out of the OnVu™ TTI. The app is developed and afterward tested in laboratory storage trials under the influence of selected environmental and technical parameters, that is, different temperature conditions, light conditions, measurement distances, and smartphone types. Based on the findings and consideration of a white balancing of color data, an accurate calculation of color data measured using the smartphone app is determined. Further storage trials under different constant and dynamic temperatures are conducted to develop a TTI kinetic shelf life model based on app color measurements. The app is further developed to provide the basis for a shelf life prediction based on the kinetic model.

In chapter 3, the current situation of temperature control systems used in food supply chains is analyzed. A survey of German companies is conducted to gather the status quo of applied temperature monitoring and data exchange systems and the use of intelligent solutions. Moreover, the use of the app-based TTI system for temperature control in different supply chains is examined. In three different supply chains (B2C, B2B, and B2C e-commerce), the application of the app-based TTI system is tested to monitor temperature conditions at different points of the supply chain and identify weak points along the chain.

In the next part of the thesis, chapter 4, the app-based TTI system is tested in a German B2C supply chain of raw pork sausage to monitor temperature conditions along the transport and storage and the shelf life prediction of the product. A kinetic shelf life model of raw pork sausage is developed based on the growth of lactic acid bacteria examined in storage trials at different constant and dynamic temperature conditions. In a pilot study, the real-time shelf life prediction of raw pork sausage based on TTI app measurements is tested at different steps and after storage under varying temperature conditions. Based on the results, the potential of the TTI system to optimize supply chain processes and reduce the upcoming amount of food waste due to more efficient processes is discussed.

Lastly, chapter 5 focuses on the investigation of the app-based TTI system for temperature monitoring and shelf life prediction in a German B2C supply chain of ready-to-eat (RTE) salad. A kinetic shelf life model of the product is developed based on the growth of the total viable count investigated in storage trials at different constant and dynamic temperature conditions. In a pilot study, the real-time shelf life prediction of ready-to-eat salad based on TTI app measurements is tested at different steps and after storage under varying temperature conditions. The potential of the TTI system to optimize supply chain processes and reduce the upcoming amount of food waste with focus consumer storage processes and consumer acceptance is discussed.

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2 Development of a novel app-based system for the digital color read-out of time-temperature-indicators and to monitor shelf life along the chain

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2.1 Abstract

The aim of this study was the development of an app-based system for the digital read-out of time-temperature-indicators (TTI) and the shelf life prediction of perishable products. The study was subdivided into four parts: development of a color measurement app for TTIs, investigation of the influence of different environmental and technical parameters on measurement accuracy, development of a kinetic shelf life model for the TTIs by app measurement and the integration of the model and a QR code scanner in the app for shelf life prediction. The study revealed the possibility to perform accurate color measurements by app. Measurement accuracy could be enhanced by white balance correction. Shelf life modeling using the Logistic and Arrhenius models resulted in activation energies from 107.49 to 111.55 kJ/mol for different charging times (1800–500 ms). The app is a promising system for stakeholders to perform temperature monitoring and shelf life prediction along the supply chain.

2.2 Introduction

Time-temperature-indicators (TTI) are simple and cost-effective tools for temperature monitoring and shelf life prediction along supply chains of perishable goods. The emerging technology provides promising opportunities to enhance food quality and safety as well as to reduce food loss and waste during distribution and at logistics, retailers and consumer level (Ellouze et al., 2011; Kreyenschmidt, Christiansen, et al., 2010; Taoukis & Labuza, 1989a; Tsironi et al., 2008). The principle of TTIs is based on a simple color change which represents history of time and temperature along storage and indicates cold chain interruptions. For several years, a high quantity of TTI systems was developed (Kerry et al., 2006; Labuza & Fu, 1995; Taoukis et al., 1999) and the feasibility of their implementation was shown in studies for, e.g., meat, chicken and fish supply chains (Brizio & Prentice, 2014; Ellouze & Augustin, 2010; Giannakourou et al., 2005; Tsironi et al., 2008). The interest in the commercialization of intelligent packaging systems is rising even though an overall implementation into processes is difficult despite enhanced computer and information technology (Fang et al., 2017; Soltani Firouz et al., 2021; Yam et al., 2005). An efficient temperature monitoring and traceability system with access to real-time data is needed to deliver high quality and safe products, however, standardized data exchange and communication between stakeholders is still challenging but necessary (Eden et al., 2011; Mack et al., 2014; Mercier et al., 2017; Raab et al., 2011).

Increasing digitalization and the application of cloud computing services enable real-time shelf life prediction which improves logistic processes and reduces food waste by dynamic pricing strategies (Corradini, 2018; Tamplin, 2018). These advantages compensate for the higher costs of single packaging monitoring. Digital data management in food supply chains is currently mainly based on the use of barcode systems that enable the storage of a high amount of individual data (Ghaani et al., 2016; Kuswandi & Jumina, 2020) like product information on batch, production and packaging date (Mercier et al., 2017; Müller & Schmid, 2019). The combination with intelligent systems can provide additional information about the supply chain, temperature history and finally real-time remaining shelf life based on the TTI discoloration kinetics.

Color measurements of TTIs are currently either done visually or with high-precise but expensive and elaborate devices, as colorimeters and spectrophotometers. Visual assessment of the TTI color is linked to the comparison with a reference color (Maschietti, 2010; Poyatos-Racionero et al., 2018), which is both qualitative and subjective, and furthermore, provides no data which could be integrated in traceability and information management systems. Colorimeters and spectrophotometers require a proper education and handling in a laboratory environment, and the integration into established process controls and stock management is complex. With ongoing digitalization processes, widely distributed smartphones obtain the advantageous property of high-resolution camera systems for color capture (Franca & Oliveira, 2021). Color values of digital images are represented in the red, green, and blue (RGB) color space on a pixel level and are more accurate, informative and can be better characterized which facilitates the implementation of standardized color image systems (León et al., 2006). Additionally, smartphones offer a continuous wireless internet connection and cloud computing services which enable the transfer of measured data to standardized traceability systems (Rateni et al., 2017). This is a decisive advantage for TTI read-out solutions, as, beside costs, high entry barriers, and complex requirements of heterogenous supply chains (Gao et al., 2020; Ghaani et al., 2016), especially technical barriers (Albrecht et al., 2020; Realini & Marcos, 2014) are the reason for a still missing successful implementation. However, challenges in the use of smartphone cameras are a uniform illumination, the white balance of camera systems as well as varying and constantly changing hardware and software systems (Hunt & Pointer, 2011; Rateni et al., 2017). These challenges must be overcome to implement a reliable and user-friendly app-based read-out system for TTIs to control product quality, support decision processes along the supply chain and to reduce the amount of food waste.

Thus, the aim of this study was the development and investigation of a novel, app-based digital color read-out system for TTIs to control the temperature along the supply chain and to predict remaining shelf life based on TTI discoloration. For this purpose, a color measurement app for TTIs was developed and afterward tested in storage trials under the influence of various environmental and technical parameters. After a white balance correction of the color values based on the results and further adjustments of the app algorithms, storage trials were conducted to develop a kinetic shelf life model based on the TTI discoloration measured by app. The color measurement app was then further developed to a shelf life prediction app by integrating the model and further measurement parameters like timestamp, geodata and product specific information which can be used for calculating remaining shelf lives along the entire chain. A QR code scanner was additionally integrated to combine color data and information for each product unit and transferring them into a cloud system. Color measurements in the storage trials were parallelly measured by colorimeter as reference.

2.3 Materials and methods

2.3.1 Experimental design

The study consisted of four consecutive experimental parts (Figure 2.1). At first, a color measurement app was developed to enable a digital readout of color data of the OnVu™ TTI by smartphones. App measurements were accompanied by a conventional colorimeter as reference in all further steps. In the second part, storage trials with TTIs were conducted to test the influence of different environmental and technical parameters on color measurements by app: TTIs were activated with different charging energies and stored under various constant temperature conditions and different light conditions, measurement distances and smartphone types were tested. Based on that, a corrected calculation of color data by white balancing was defined to reduce the influences of parameters. The trials were conducted by using the OnVu™ TTI labels already available on the market. Additionally, advancements of the TTI design were developed to enable an input into digital systems via QR code. In the third step of the study, storage trials with the OnVu™ TTI were conducted to develop a kinetic shelf life model based on the TTI discoloration measured by app. TTI labels were therefore activated with various charging energies and stored under different constant and dynamic temperatures. Based on the measurements in step 3, data and shelf life models were integrated into the app in the fourth part to use it as a shelf life prediction tool along the entire supply chain. Besides the TTI measurement, the app comprehends the display of the predicted remaining shelf life and usability features such as a drop-down menu to select the specific supply chain step and a QR code scanner for a correct allocation of color data to specific product information and an individual serial number. All TTI trials were accompanied by an ongoing development process of the app to enhance accuracy of color measurements, i.e., the adjustment of algorithms and an automated color selection.

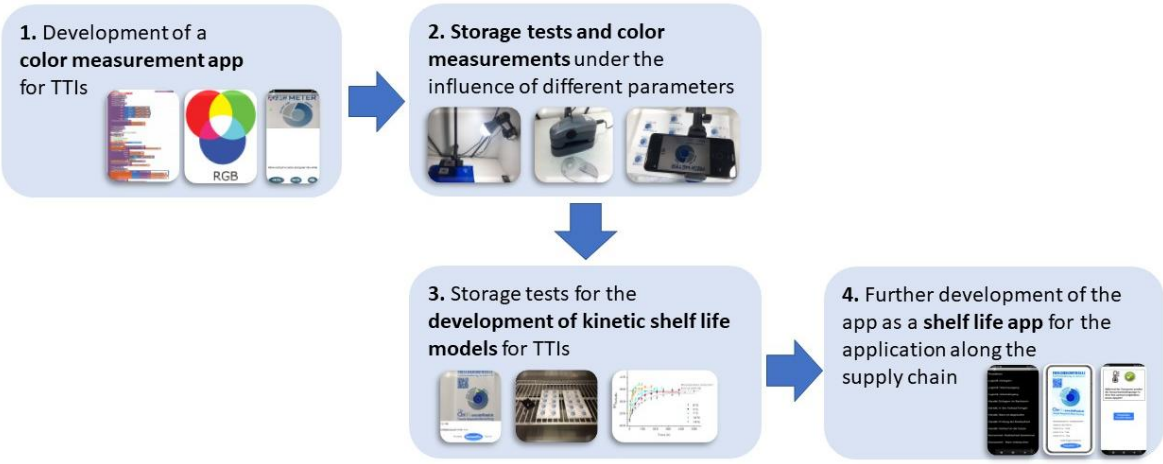


Figure 2.1. Process flow of the study

2.3.2 General activation and measurement process of the OnVu™ TTI

For all investigations, the OnVu™ TTI (Ciba Specialty Chemicals & Freshpoint, Basel, Switzerland, patent WO/2006/048412) was used. The well investigated label is already on the market and based on a pigmented water ink which is activated by UV light (Kreyenschmidt, Christiansen, et al., 2010). The color of the label changes from blue to white. The amount of UV light influences the length of the discoloration process and the initial color of the label after activation. The labels were activated by a UV light charger (GLP 80/56 TTI, Bizerba, Germany) in a cooling chamber (Viessmann GmbH & Co KG, Hof, Allendorf, Germany) at 4.0°C ± 0.5. After activation of the pigmentary water ink in the center of the label, a protective UV filter (LOT# 000018272) was automatically applied by thermal transfer print. After charging, the labels were placed on precooled glass plates (4 mm thickness) with two layers of self-adhesive white paper to ensure a consistent background for the color measurements. The labels were afterward stored in high-precision low temperature incubators (MIR 153, SANYO Electric Co., Ora-Gun, Gumma, Japan) at selected temperatures. Temperature and humidity conditions were measured by data loggers (174 H, Testo SE & Co. KGaA, Titisee-Neustadt, Germany) at intervals of 5 min.

The TTI discoloration was measured immediately after charging and at defined interval points during storage. Color measurements by app (from now on referred to as app measurement) were conducted in a darkroom to create a uniform environment for a standardized assessment of the influence of parameters as light and distance on app measurements. Parameters could be adjusted more flexible for a more realistic setting in comparison to illumination chambers and black boxes normally used in laboratory studies (Cruz-Fernández et al., 2017). For app measurements at daylight conditions a daylight lamp (1620 Lm, 6500 K, Tageslichtlampen24.de, Kiel, Germany) was positioned in a way that sufficient light was provided without casting shadows on the photograph. The smartphones were positioned in a fixed holder to achieve reproducible measurements. The TTIs were positioned in parallel to the smartphone below the lens. As reference values, discoloration of TTIs was measured in CIELAB color system (from now on referred to as reference measurement) by colorimeter EyeOne i1 Basic Pro3 (X-rite Europe GmbH, Regensdorf, Switzerland) using the software i1Profiler v3.3.013493 (X-rite, Inc., Grand Rapids, Michigan, US) for the analysis.

2.3.3 Experimental parts of the study

2.3.3.1 Development of a color measurement app for TTIs

The smartphone app was specifically developed for the color measurement of the OnVu™ TTI for Android operating systems and was programed by using the MIT App Inventor (Massachusetts Institute of Technology, USA). Smartphone and camera specific data are saved on the smartphone when the app is installed by taking an arbitrary picture during the first installation. By starting the app, the camera system of the smartphone is opened automatically, and an instruction appears to take a picture of the TTI and to measure its color values in the RGB color space. After taking the picture of the TTI, the blue dot in the center of the label is selected manually by moving a cursor to the respective position. A white point at the edge of the label is selected by a second cursor which is needed for the white balancing of the raw blue color value to correct the influence of environmental conditions. About 100.000 pixels are gathered depending on the specific smartphone and its settings. Based on the gathered pixels and in combination with the smartphone and camera specific numbers, the app algorithm calculates RGB color values for the blue dot in the center ($R_bG_bB_b$) and the white points on the label ($R_wG_wB_w$). Color values are saved in data files on the smartphone. The app development was accompanied by test measurement procedures of TTIs at different stages of coloration, such as the point of activation and complete discoloration.

2.3.3.2 Storage tests with color measurement app and reference system under the influence of different environmental and technical parameters

Storage tests with TTIs were conducted to analyze the influence of different environmental and technical parameters on app measurements, which are charging time, temperature, light, measurement distance and smartphone type. Based on the results, a corrected calculation of color data by white balancing was determined to minimize the influences of parameters on app measurements. For this study part, the OnVu™ TTI label "Fresh-Meter" (Batch 29.08.2014, Color Batch 00552HN8) was used. In total, 60 labels (ten labels for each charging time and temperature) were activated at two different charging times (1800 milliseconds (ms), 1130 ms) and stored at three different isothermal temperatures (4°C, 7°C, 15°C). App measurements in the darkroom were conducted under two different light (daylight lamp, ambient light) and two distance conditions (10 cm distance, 10 cm distance with 2x zoom) by two different Android based smartphones, Nokia 7.2 Dual-SIM Android™ 9.0 48 m pixels (Nokia Oyj, Espoo, Finland) and XIAOMI Mi Note 10 Lite 64 MP quad Camera (Xiaomi Inc., Beijing, China). Each parameter combination of charging time, temperature, light, distance and smartphone type were tested. Consequently, 80 app measurements were made at each investigation point. Reference measurements by colorimeter were conducted at the same investigation points. Based on app measurements, the medians of the single R, G and B values for the blue dot (R_b; G_b; B_b) and the white color point (R_w; G_w; B_w) were built. The square value SV_{RbGbBb} for raw color data of the blue dot was then calculated.

$$SV_{R_bG_bB_b} = \sqrt{{R_b}^2 + {G_b}^2 + {B_b}^2} \tag{2.1}$$

where R_b ; G_b; B_b: raw values for the blue dot.

Color data for the blue dot were then corrected by white balance to eliminate influences of investigated parameters. Therefore, measured raw data of R, G and B values for the white color points were each subtracted from the absolute white value 255. The corrected RGB white values were each added to the measured RGB color values of the blue dot.

$$R_c = (255 - R_w) + R_b \; ; \; G_c = (255 - G_w) + G_b \; ; \; B_c = (255 - B_w) + B_b \tag{2.2}$$

where R_c; G_c; B_c: corrected color values by white balance; *255*: absolute white; R_w; G_w; B_w: raw values for the white color points.

The square value SV_{RcGcBc} was then calculated with the corrected RGB color values.

$$SV_{R_cG_cB_c} = \sqrt{{R_c}^2 + {G_c}^2 + {B_c}^2} \tag{2.3}$$

The square value SV_{LAB} based on the reference measurements was calculated according to Kreyenschmidt, Christiansen, et al. (2010).

$$SV_{LAB} = \sqrt{L^2 + a^2 + b^2} \tag{2.4}$$

where *SV*: square value; *L*: lightness/luminance; *a*: red and green component; *b*: yellow and blue component of the color.

Based on the measured data, the color measurement app was further improved by adjusting the algorithms used for color measurements. Consequently, the relevant blue and white areas were selected automatically after photographing. The software also evaluated variations of the relevant RGB data, e.g., caused by effects while the TTI was printed, by shadows on the pictures or because the TTI was folded, to calculate the RGB data more reliably.

2.3.3.3 Development of a kinetic shelf life model for the OnVu™ TTI based on app measurements

For the implementation in digital processes, a new batch of the OnVu™ TTI ("Frischekontrolle", Batch 21.06.2021, Color Batch 00552HN8) including a QR code was printed which was used for the development of a kinetic shelf life model. Scanning of the serialized QR code by the app after app measurement enables a single-product attribution to the corresponding TTI values as well as the access to individual product information. Consequently, it is possible to transfer and recall color values and product information into a database in a cloud system. The labels were activated at five different charging times (500, 800, 1200, 1500, 1800 ms) and stored at five different isothermal temperatures (2°C, 4°C, 7°C, 10°C, 15°C). A dynamic temperature scenario was additionally investigated for labels charged at 800, 1200, 1500 and 1800 ms, the labels were stored at 2°C for 48 h, 7°C for 48 h, and then 10°C until the end of storage time. Eight samples were activated and measured for each charging time at each temperature, meaning 232 labels in total. The TTI discoloration of the labels was measured immediately after charging and at defined interval points during storage. App measurements were conducted with the Nokia 7.2 smartphone at constant light and distance conditions (daylight lamp and a 10 cm distance with 2x zoom). Reference measurements were conducted at the same investigation points. For the development of the shelf life model of the OnVu™ TTI, the kinetic approach as described by Taoukis & Labuza (1989a, 1989b) and Tsironi et al. (2008) was used. The data were fitted using the software Origin 8 G (OriginLab Corporation, Northampton, MA, USA), using nonlinear regression (Levenberg– Marquardt algorithm). The discoloration of the TTI by app measurements was described by the development of the RGB and CIELAB square values for app and reference measurements, respectively, as function of time. For both calculations, a logistic model as the primary model was used (Kreyenschmidt, Christiansen, et al., 2010).

$$SV_{LAB;\,R_cG_cB_c} = \frac{a}{1 + e^{-k(t-xc)}} \tag{2.5}$$

where a: amplitude; k: reaction rate (h^{-1}); xc: reversal point (h); t: time (h) for each logistic model in CIELAB and RGB color systems.

The time when a defined discoloration end point was reached, which corresponds to the TTI shelf life, could be calculated with the fitting results by plugging in the discoloration end point. The end point was known as SV_{End} = 71 for reference measurements in CIELAB color system (Kreyenschmidt, Christiansen, et al., 2010). For app measurements in RGB color system, the end point was calculated as SV_{End} = 344 with a correlation of SV_{LAB} values with the corresponding SV_{RcGcBc} values at different temperatures, using a polynomic trendline.

$$t = -\frac{\ln(\frac{a}{SV_{End}} - 1)}{k} + xc \tag{2.6}$$

where SV_{End}: 71 for TTI shelf life calculation in CIELAB color system, 344 in RGB color system.

The temperature dependency of the TTI discoloration in each color system was described using the Arrhenius equation (modified after Arrhenius, 1889) as secondary model and plotting the calculated reaction rate k as a function of temperature.

$$\ln(k) = \ln(k_0) - \frac{E_a}{R} \cdot \frac{1}{T} \tag{2.7}$$

where k: reaction rate (h^{-1}); k_0: constant (h^{-1}); E_a: activation energy (kJ mol^{-1}), R: ideal gas constant (8.314 J mol^{-1} K^{-1}); T: absolute temperature (K).

2.3.3.4 Development of the app as a shelf life predicting tool

Based on the parameters of the developed kinetic shelf life model, the app was finally adjusted to predict the shelf life based on TTI color values. Kinetic model parameters were included into the app to calculate remaining shelf lives for different temperatures. The app was further extended by a drop-down menu prior to the photographing to select a user profile, i.e., production, logistic, retailer, consumer. Furthermore, an app-specific cloud database was constructed. The serialized QR code of the TTI label is scanned automatically by using the app. Thus, the serialized number of the QR code is used to get product specific parameters necessary for the shelf life model out of a database via internet. For each scanning process of the same TTI with its serialized QR code, a new data set with the new color values and updated parameters is saved in the same database, related to the serial number within the QR code. For the use of the shelf life app, an internet connection is required.

2.4 Results and discussion

2.4.1 Development of a color measurement app for TTIs

The developed algorithms focused on different data processing steps after a TTI picture was taken: the identification of RGB color values in the blue dot, the localization of the color circle surrounding the blue dot as well as representative white areas on the label, and the storage of identified RGB values in data files to be usable for further calculations. Results showed that the development of a color measurement app was successfully reached. The app is in general able to detect and measure individual R, G and B values of the TTI and to reflect variances in color values. The change of color values in RGB system from blue at the activation point to complete discoloration was measurable by app. Therefore, the behavior of app measurement conformed to the typical measurement by colorimeter in CIELAB color system which is the current standard method (Albrecht et al., 2020; Gao et al., 2020; Kreyenschmidt, Christiansen, et al., 2010). Thus, the basic prerequisites for a successful app measurement of the TTI color are given. It can be assumed that color measurements with a smartphone app are sensitive enough to reliably measure discoloration of TTIs along time.

2.4.2 Storage tests with color measurement app and reference system under the influence of different parameters

App measurements revealed that raw color values in the blue dot of the label under the influence of the different parameters light, distance and smartphone type showed moderate to high variations. Raw color values in the blue dot measured under the influence of the different parameters were pooled to reflect their overall variation. (Results for measurement at daylight conditions with 10 cm distance with Xiaomi could not be calculated for all investigations, as values for the white color points were not detected by the picture). This is shown exemplary for selected points of time for measurements at 7 °C in Figure 2.2a. Here, raw SV_{RbGbBb} values were in a range from 94.46 to 183.29 at the initial charging point and 217.46 to 312.58 after 360 h. Concerning light conditions, measurements at daylight (lamp) showed higher color values over time than at ambient light (see Appendix, Table A.1). Also, measurements with 2x zoom showed higher color values than with the usual distance of 10 cm at the same light conditions. Measurements by Xiaomi showed tendentially higher color values than by Nokia, however, in the later course of storage time, values are increasingly approaching each other. Highest variations are shown for measurements at ambient light with Nokia compared to measurements at daylight lamp conditions and zoom with Nokia in all scenarios at different charging times and temperatures.

The high variance in the results for raw RGB data of the blue dot indicated that an inclusion of the white balance and the correction of app measurements was necessary to reduce the parameter influences. The high quantity of data generated by the multiple app measurements at different conditions were the basis for developments in measurement corrections and app improvements. The app measurement correction by white balance, also shown in Figure 2.2a as pooled data for the different parameter conditions, showed a clear reduction of data variance when compared to raw data at 7 C. Corrected SV_{RcGcBc} were in a range from 230.21 to 270.46 at the initial charging time and 362.01 to 414.84 at 360 h. The differences in the absolute numbers result from the correction of measurements. The courses of discoloration at different parameter settings are shown in Figure 2.2b, exemplary for 1800 ms charging time and storage at 7°C. Initial SV_{RcGcBc} color values ranged from 232.81 ± 3.42 for Nokia at ambient light to 263.88 ± 2.97 for Xiaomi at daylight lamp with 2x zoom. SV_{RcGcBc} color values after storage of 479 h at 7°C ranged from 395.15 ± 9.13 to 406.20 ± 5.82 for Nokia at ambient light and Xiaomi at ambient light, respectively. Corrected color values are still higher measured at daylight than at ambient light conditions, however, differences are remarkably reduced. Differences in distance could be nearly compensated by data correction. App measurements by Nokia at the different conditions were still generally lower than by Xiaomi, but differences were strongly reduced.

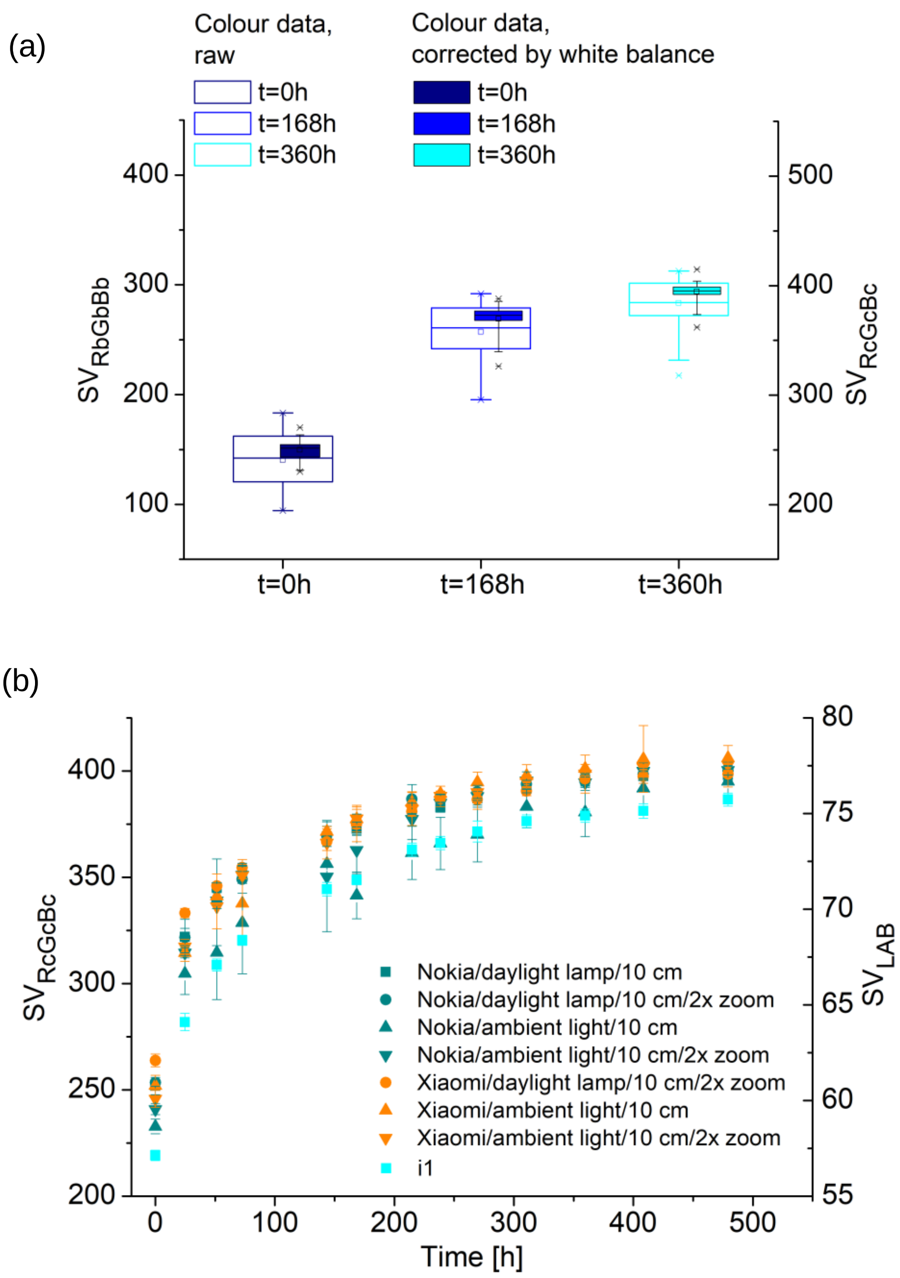


Figure 2.2. (a) Boxplots of raw color data and color data corrected by white balance measured by app (n=80). (b) Comparison of TTI discoloration measured by app at different ambient and smartphone conditions and by colorimeter at different points of time during storage at 7°C (TTI charging time: 1800 ms, n=10 per measuring point)

Furthermore, overall variances for corrected values at the different parameter settings decreased throughout the storage time, assuming that the sensitivity decreased at high discoloration. However, this range in which the TTI is already discolorated is not relevant for the shelf life prediction. Additionally, SV_{RcGcBc} values showed good reproducibility for constant temperatures in all investigations with standard deviations (SD) in a range from 1.41 to 10.04 immediately after charging (0 h) and 0.78 to 30.85 for the entire app measurement points. For reference measurements with colorimeter, stable and reproducible TTI color values were already presented by (Kreyenschmidt, Christiansen, et al., 2010). SDs are higher for app measurements, however, 75 % of SDs are under 4.34 for start values at 0 h and under 7.46 for entire measurements. A further optimization of the app could achieve the measurement of more stable color values. The influence of these variances on a later shelf life prediction depends on the environmental conditions and the regarded product and must be investigated in practical studies.

In general, it can be assumed that the calculation via subtraction of white balance is a reliable way to correct app measurements. Also Lee, Park, et al. (2019) and Park et al. (2014) applied a normalizing of RGB color measurements with white background when investigating paper microfluidics and freshness indicators, respectively. Prior to the definition of the correction with white balance in this study, various calculation paths were analyzed. The calculation determined in equation 2.2 showed the best adjustment of RGB values when comparing the results of the different parameter combinations. Smartphone and camera specific data were already taken into account in measurements when installing the app. However, it must still be considered that there is a complexity of influencing factors on app measurements based on the individual properties of camera systems and smartphones. One solution to further optimize app measurements and reduce variation due to influencing parameters is to implement a smartphone and camera specific correction factor which automatically corrects measurements after photographing. It can be further concluded that a reproducible and reliable setting of the initial color values can be also validated by app measurement. The application of a smartphone is even more advantageous due to the detection of the whole blue color dot by photographing; most conventional colorimeters only gather a smaller, more unrepresentative surface area (León et al., 2006; Papadakis et al., 2000; Segnini et al., 1999).

2.4.3 Development of a kinetic shelf life model for the OnVu™ TTI based on app measurements

Figures 2.3a and b show the discoloration processes of the TTI initially charged for 1800 ms and stored at different constant temperatures by app measurements as well as in comparison to reference measurements. The course of the discoloration curves is in general comparable to the results in the previously described experimental part. Furthermore, the distinction of initial charging values and associated discoloration times could be reliably reached by app measurements in all investigations. The results are exemplary shown in Figure 2.4a for charging times at 7°C, Figure 2.4b shows results of reference measurements. Results of the dynamic temperature scenario also showed that temperature fluctuations – as they can occur under real supply chain conditions – could be reflected by the app. The kinetic shelf life models based on app measurements could be likewise generated with the same logistic regression as reference measurements. This is the basic requirement for the application of the app as detection device, as kinetics are detectable and shelf life measurements are possible. Discoloration curves generated by app measurements flattened out faster and plateaus are reached earlier along time when compared to reference measurements. Consequently, discoloration end points were partly not reached at high charging times and low temperatures in the applied storage time. Results indicate that the RGB color system is less sensitive for changes in the lighter color range. The less sensitivity can limit the range in which the model based on app measurements could be reliably used for shelf life prediction, which means that at very high charging times and low temperatures, a shelf life prediction is currently limited.

The lower sensitivity of smartphones compared to high-precise, analytical devices is another limitation in the applicability. Also extreme light conditions can influence the accuracy of the measurements. One possibility would be to indicate suitable conditions, like other sensitive measuring systems. However, in general, the results showed that the TTI color measurement by an app-based read-out system is possible, which is a milestone in the development of easy-to-use TTI systems in practice. An optimization of the models could enhance the accuracy of the shelf life prediction and thus, could make the system more applicable in terms of safety.

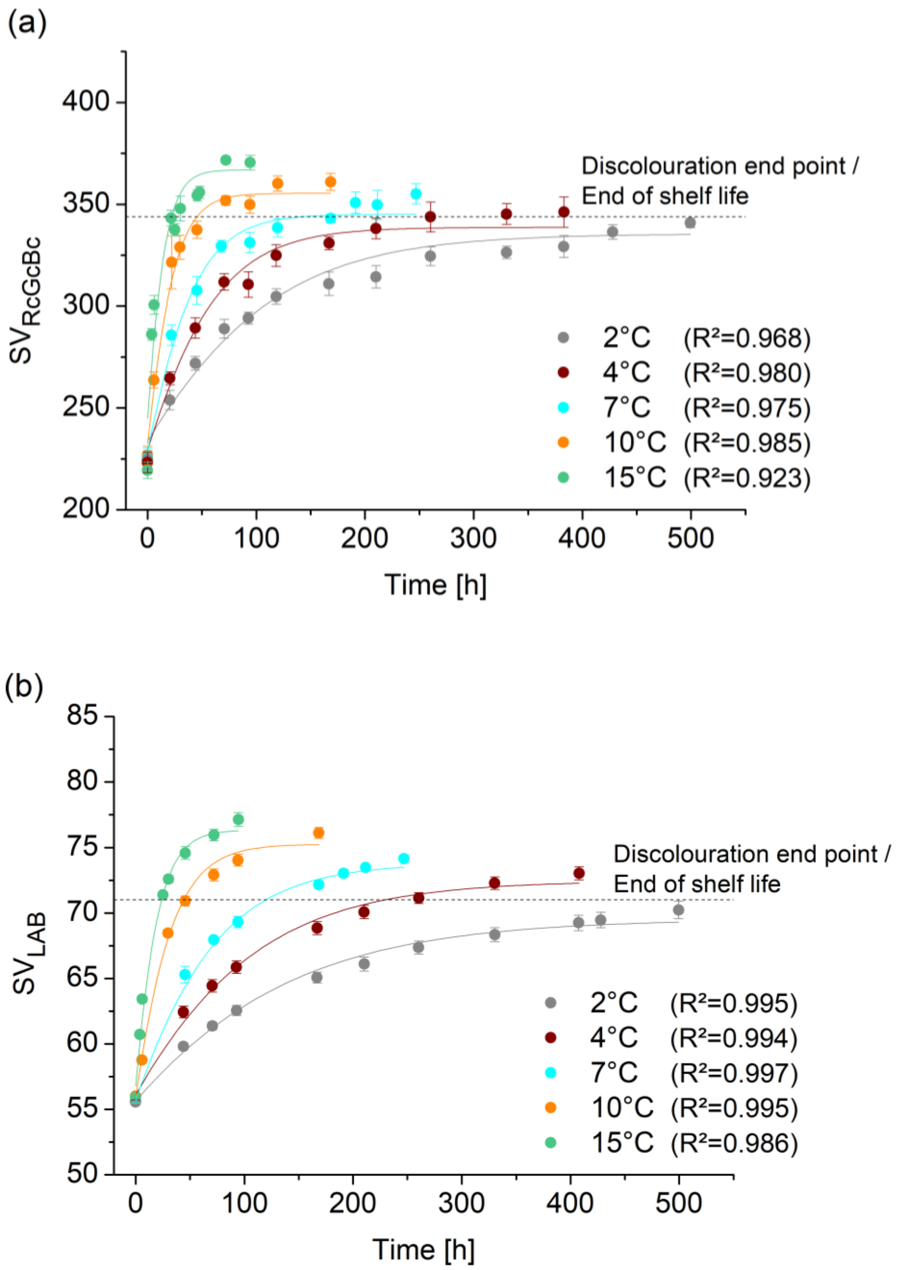


Figure 2.3. Discoloration of the TTI stored at different temperatures for a charging time of 1800 ms (n=8 per measuring point). (a) measured by app. (b) measured by colorimeter

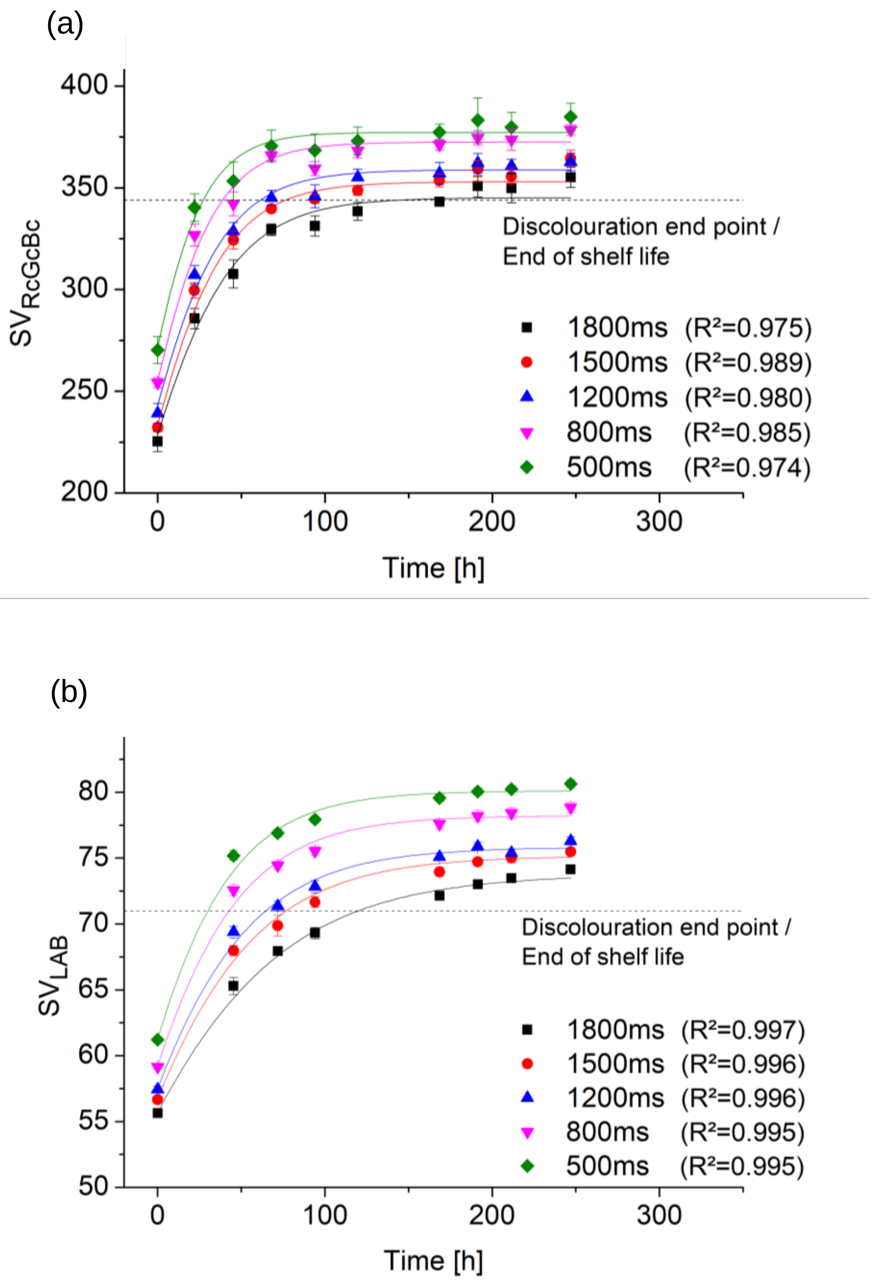
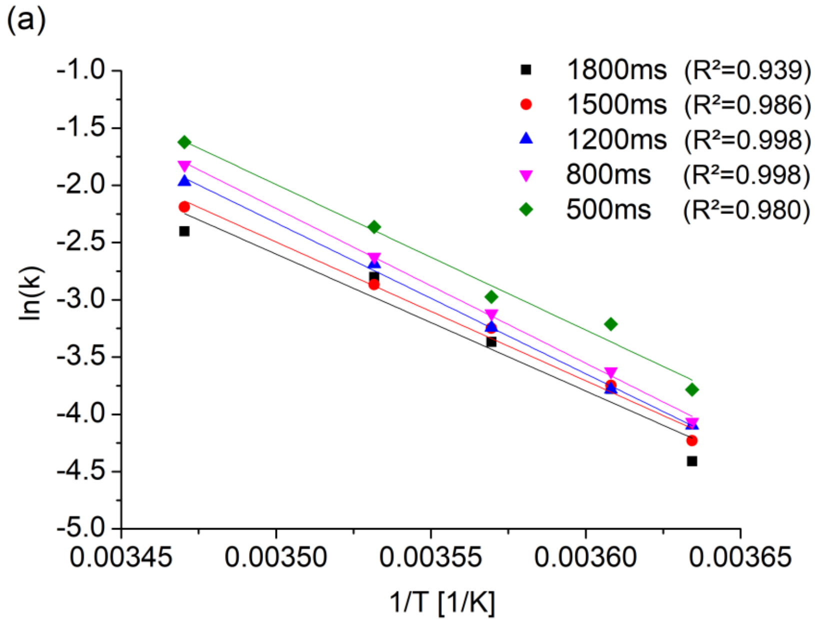


Figure 2.4. Discoloration of the TTI by using different UV charging times stored at 7°C (n=8 per measuring point). (a) measured by app. (b) measured by colorimeter

The kinetic behavior of the TTI with its discoloration measured by app is shown in Figure 2.5a as the temperature dependency of the reaction rate based on the Arrhenius approach. Results for ln(k) at different temperatures were fitted by linear regression. The lines ran almost parallel to each other, depending on the individual charging time. Linear fits for 1800 to 800 ms converged with lower temperature dependency. The Arrhenius model for parameters resulting from reference measurements showed comparable linear fits (Figure 2.5b). Values for ln(k) were higher for app measurements with -1.62 to -4.41 when compared to reference measurements with -2.19 to -4.75. Results are not directly comparable due to the different color systems resulting in different number ranges for model parameters a, xc and k. However, the slopes of the linear fits were in a similar range (Table 2.1a), which is the basic prerequisite for the calculation of the activation energies as the expression of the temperature dependency of discoloration.



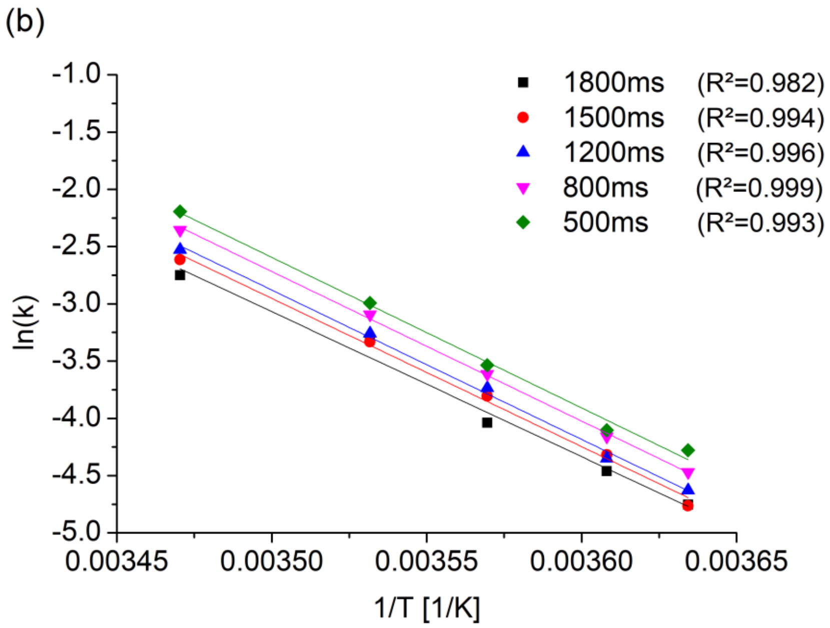


Figure 2.5. Arrhenius plot showing TTI temperature dependency of the reaction rate (*ln(k)*) at different charging times for measurement with (a) app and (b) colorimeter (n=8 per measuring point)

The activation energies for the different charging times calculated based on app measurements were in a range from 107.49 to 111.55 kJ/mol (25.69 to 26.66 kcal/mol). Activation energies calculated based on reference measurements differed from 101.46 to 114.68 kJ/mol (24.25 to 27.41 kcal/mol). The similarity of calculated results proves that the discoloration process and the kinetic behavior of the TTI could also be mirrored and reliably calculated by the app. Kreyenschmidt, Christiansen, et al. (2010) reported activation energies in a range from 92,9 to 105.9 kJ/mol by colorimeter measurements. Slightly higher activation energies in this study may be due to a different range of charging times and the usage of novel printed batches of the OnVu™ TTI, resulting in differing discoloration times and thus, in various kinetic parameters.

It is known that activation energies of TTI and the monitored food should not differ more than 20 kJ/mol (Taoukis et al., 1999). The calculated activation energies based on app measurements also fulfilled the requirements for the TTI to be applied as a temperature monitoring tool for perishable products. The TTI characterized by app measurements can thus represent a wide variety of perishable products in the range of comparable activation energies. This includes aerobe packed fresh poultry with 101.3-102.9 kJ/mol (Bruckner et al., 2013; Raab et al., 2008), cooked meat products with 109.9-115.9 kJ/mol (Kreyenschmidt, Hübner, et al., 2010; Mataragas et al., 2006), MA packed fish 106.7 kJ/mol (Labuza et al., 1992), as well as ready-to-eat meals with 105.58 kJ/mol (Haouet et al., 2018), calculated based on the individual spoilage kinetics of the products.

2.4.4 Development of the app as a shelf life predicting tool

Shelf lives calculated by app and reference measurements are shown in Table 2.1b. Differences in shelf lives between app and reference measurement varied between 69 and 0 h, differing rather at 2°C–4°C (6–69 h) than at 7°C–15°C (0–2 h). This could be based on differences in linear fits and increased slopes of the discoloration kinetics by app measurement in the first half of the storage time at lower temperatures. At higher temperatures, the curves are more similar to reference measurements. Also at the dynamic scenario, shelf lives at different charging times had low differences between 1 and 9 h. Further developments in the camera and app technologies may enhance the color sensitivities and improve the reflection of TTI discoloration kinetics. There are already developments in the field of app-based TTI read-out and for barcode scanning, as for the Smartdot TTI (Evigence, 2022) and the Smart Tag™ (Freshcode) (Packaging Journal, 2019), respectively. Chen et al. (2017) also showed that a digital read-out of food sensors by smartphone is possible and gives reliable information about food spoilage. It is generally conceivable that the developed app can also be applied for other TTI systems with a color-based response. These could include systems based on discoloration or color change, such as described for the Vitsab® Smart Labels (Chun et al., 2013; Tsironi et al.,

2016) or newly developed TTI materials as studied by Xu et al. (2017) and Brizio & Prentice (2015). The conversion of previously applied color response based on CIELAB system to RGB system as a digital response is mandatory.

Table 2.1. (a) Kinetic parameter of the OnVu™ TTI and R^2 values for constant temperature conditions at different charging times for measurement with app and colorimeter. (b) Shelf life of TTI calculated by app and colorimeter measurements for different constant temperature conditions at different charging times

(a)

Charging time [ms]	TTI measurements with app [SV_{RcGcBc}]			TTI measurements with colorimeter [SV_{LAB}]		
	Slope	**E_a [kcal/mol]**	**R^2**	**Slope**	**E_a [kcal/mol]**	**R^2**
1800ms	-12667.11	25.69	0.982	-11260.10	24.25	0.939
1500ms	-12945.76	26.25	0.994	-12199.24	24.74	0.986
1200ms	-13046.43	26.46	0.996	-13182.46	26.73	0.998
800ms	-13065.08	26.49	0.999	-13516.21	27.41	0.998
500ms	-13145.83	26.66	0.993	12710.27	25.78	0.980

(b)

Charging time [ms]	TTI shelf life based on app measurements [h]						TTI shelf life based on colorimeter measurements [h]					
	2°C	4°C	7°C	10°C	15°C	dyn	2°C	4°C	7°C	10°C	15°C	dyn
1800ms	-	-	145	46	22	140	-	229	120	44	24	149
1500ms	-	159	77	42	18	138	451	153	77	39	18	137
1200ms	-	116	61	28	13	108	275	130	65	31	14	111
800ms	128	73	39	22	9	97	197	94	43	22	10	90
500ms	70	44	27	13	6	N/A	102	60	30	15	7	N/A

The increased popularity of smartphones as a simple, time- and cost-effective digital picture and data recording device can revolutionize the developments in intelligent packaging research (Poyatos-Racionero et al., 2018), especially when combined with big data and cloud computing (Kalinowska et al., 2021). The visual TTI assessment has an influence on the consumer behavior and product handling and could provoke rejection and cherry-picking effects (Müller & Schmid, 2019; Rossaint & Kreyenschmidt, 2015), but the objective analysis by using a smartphone – as a well-established device – may enhance consumer's trust. Furthermore, hurdles in implementation, such as additional costs and a simple operation for the stakeholders, are relatively low. The promising application of smartphones as color and image analysis tools was already shown in other studies, especially for the assessment of food quality parameters (Franca & Oliveira, 2021), such as fat contents (Cruz-Fernández et al., 2017), ethanol concentration in alcoholic beverages (Böck et al., 2018; Marinho et al., 2019) or quality assessment of tea (Li et al., 2021). Digital imaging with smartphones was also studied for indirect food control, such as freshness indicators and paper-based assays (Lee, Baek, et al., 2019; Lee, Park, et al., 2019; Shen et al., 2012).

Figure 2.6 shows the overall shelf life app system developed in this study which combines different functionalities that may be used along the supply chain of perishable products: Products are packed and labelled with TTIs including the QR code which enables an individual serial number, whereby traceability of single products can be realized (Kalpana et al., 2019). The producer is authorized to enter product and batch specific information via the web application into a data base for the defined TTIs and serial numbers used for this batch. This includes product shelf life data necessary to estimate the remaining shelf lives along the chain; it also may include additional information for marketing or logistic activities of stakeholders. While scanning the QR code, the app is connected via internet to a database and user information, the current location, a timestamp, and product specific information are added to the TTI serial numbers. The app can be customized for different stakeholders, as logistic partners, wholesalers, or customers, by adjusting different information access, functionalities, authorizations, and outputs. The provision of valuable supply chain information for relevant stakeholders makes the entire supply chain more transparent and can thus optimize processes. Combining TTI systems with barcodes enables the integration of more useful information complementing the color measurements which optimizes the whole temperature monitoring process (Fang et al., 2017; Wang et al., 2015).

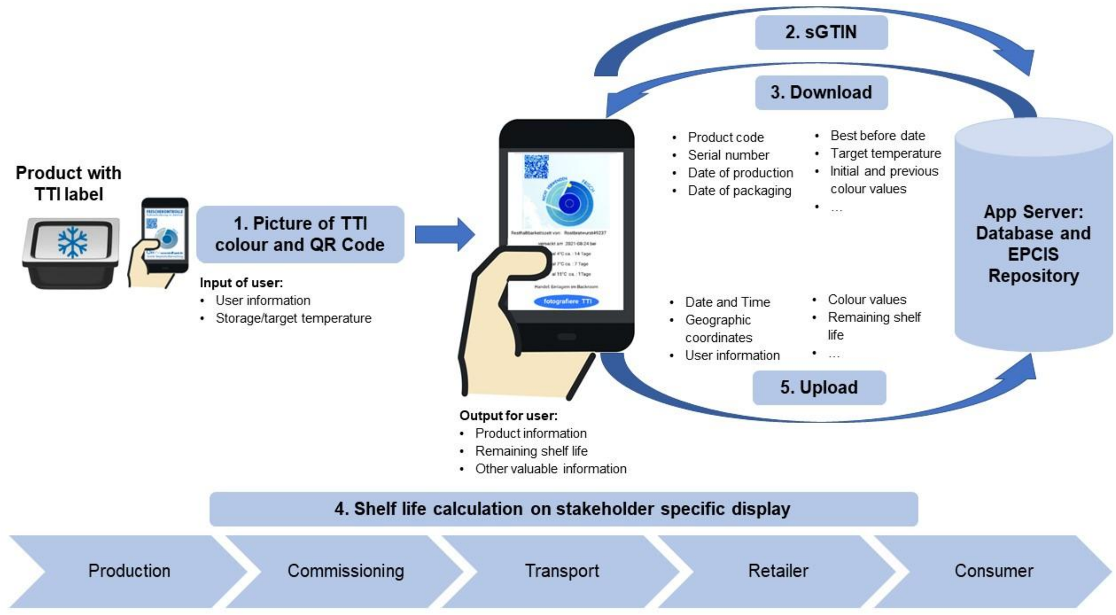


Figure 2.6. Overview of the app system for smartphone application along the supply chain of perishable food products

2.5 Conclusion

In this study, a novel app-based system for the color measurement and shelf life prediction of TTIs was developed. It was found that a reliable app measurement with digital imaging of TTIs is possible by a white balanced calculation of RGB color values. The kinetic shelf life model based on TTI discoloration by app measurement showed comparable results in activation energies compared to the reference measurements by colorimeter. The inclusion of a QR code into TTI systems provide a remarkable benefit concerning the connection with product-specific data and the transfer of measured color values and other real-time supply chain data into a cloud. The integration of the kinetic shelf life models into the app-based system could enable the use of the app as a shelf life prediction tool, which allows stakeholders along the entire chain to monitor temperature and predict remaining shelf lives by applying a smartphone as a simple measurement device. Therefore, further investigations concerning model validation and tests under real chain conditions are necessary. Further studies should examine if perishable products can be covered by the developed system. Therefore, detailed knowledge on the products is necessary, and the TTI must be customized to the product's and chain specific requirements. Thus, the app not only represents a user friendly but also a time effective solution for actors along food supply chains. The implementation of app-based TTI systems can further support the emerging idea of dynamic shelf lives.

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3 Temperature control and data exchange in food supply chains: Current situation and the applicability of a digitalized system of time-temperature-indicators to optimize temperature monitoring in different cold chains

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3.1 Abstract

The current situation of temperature monitoring in perishable food supply chains and the optimization of temperature control was studied by combining two approaches. First, a survey among German companies (production, processing, logistics, wholesale, retail) was conducted to analyze the current temperature monitoring and data management conditions as well as the use of novel monitoring systems, such as time-temperature-indicators (TTI). Second, the temperature conditions in three different supply chains (B2C for raw pork sausage, B2B for fish, B2C e-commerce for mixed products) were investigated to analyze the applicability of TTIs with an app-based read-out system to identify weak points and to optimize cold chain management under practical conditions. The results of the survey showed that mainly static conditions are tested along the supply chain. Thus, the actors rely mostly on visual inspection or best-before-date labeling while TTIs are not widely used. Currently, temperature data are barely exchanged by stakeholders. In the B2C chain, mean temperatures on different pallet levels were comparable, also reflected by TTIs and the app-based read-out system, respectively. In the B2B chain, temperature interruptions during the unloading process were detected, revealing main challenges in perishable supply chains. Temperature monitoring by TTIs on a box level was possible by positioning the label close to the product. Results in the e-commerce sector showed heterogeneous conditions in different boxes depending on initial product temperatures and loading. TTIs and the app-based read-out system showed reliable results based on different temperature scenarios, when TTIs are positioned close to the most sensitive product.

3.2 Introduction

Temperature monitoring along food supply chains is of special importance for the traceability of goods, the optimization of logistic processes and to get accurate information about the real quality of products at the point of incoming and outgoing inspection. Several studies show that temperature abuses along transports of perishable food are crucial since they affect quality and safety of food (Koutsoumanis & Taoukis, 2005; Ndraha et al., 2018; Nychas et al., 2008; Raab et al., 2008; Zeng et al., 2017). Currently, temperature monitoring systems and data exchange in food supply chains are not optimized yet (Göransson et al., 2018). Even if legal temperature requirements for perishable products do exist (The European Parliament and the Council, 2004), the full temperature history of the product is not available and the measurement of the ambient temperature can be misleading (Mack et al., 2014; Raab et al., 2011). Consequently, lots of products are wasted along the chain due to cold chain interruptions and misinterpretation of data (Canali et al., 2017; Gustavsson, 2011; Nychas et al., 2008). There is a high need for temperature monitoring systems with close contact to the product, especially for multi-step supply chains with pre-cooling, transports, transshipment, and platform points as well as storage at the retailer and consumer (Amath et al., 2021). Furthermore, appropriate measuring devices are required. As one possible solution, lots of progress has been made in the field of sensor technology. Radiofrequency identification tags (RFID) and Wireless Sensor Networks (WSN) systems are temperature monitoring and data transfer tools showing a high potential through covering the complete transport (Arnold et al., 2008; Cil et al., 2022; Eden et al., 2011; Lamberty & Kreyenschmidt, 2022). The application of IoT-based and blockchain technologies can support confidential data management and process control along distribution (Accorsi et al., 2017; Boubaker et al., 2022; Burgess et al., 2022; Zhang et al., 2017). The use of software-based systems for tracing and scanning of goods on a pallet and box level is also possible (Mack et al., 2014; Nastasijević et al., 2017) and can automatize monitoring processes by replacing paper-based documentation (Islam et al., 2022; Thakur & Forås, 2015). Until now, these technologies are not widely spread in the food industry. Main reasons are varying and complex supply chain characteristics, high implementation costs, unknown requirements of the different actors and missing guidelines for the implementation and selection of suitable technologies as well as standardized data exchange systems (Lamberty & Kreyenschmidt, 2022). Sensors are often applied only on the pallet level and do not track the history of each product within the last mile, which is the most sensitive part of the supply chain and constitutes half of its total costs (Arnold et al., 2008; Lehmann, 2017; Vanelslander et al., 2013).

Beside wireless sensor technologies, the use of time-temperature-indicators (TTI), which show the temperature history of a product by a color change, has also been discussed for more than 30 years (Taoukis & Labuza, 1989). At the moment, however, they are also not implemented in a wide range because of costs, legal issues and missing trust of stakeholders and consumers (Ghaani et al., 2016; Sohail et al., 2018). Moreover, digitalized systems for read-out are still missing and currently performed either visually or by specific measurement devices. A promising and cost-effective way for the digital read-out of TTIs is the use of smartphones, which can optimize workflows, e.g., in logistics, due to the fast exchange of measured data (Albrecht et al., 2020). TTI systems are also a promising tool for the e-commerce sector. The lack of temperature controlling in the last mile is particularly critical here, thus, retailers and parcel services hold the responsibility and must rely on each other concerning the compliance with temperature requirements (Grant et al., 2014; Moriset, 2020). Online ordered perishable food products are usually delivered in passively cooled boxes with mixed products in different quantities and with various initial temperatures. Depending on the design of the box and the temperature of the different products, there is a risk for an increasing temperature of the fresh produce and, thus, a decrease in freshness. Therefore, monitoring the temperature in the last mile is of high importance.

Currently, TTI solutions are moving more into the political and industrial discussion due to the emerging food waste problem (Poyatos-Racionero et al., 2018; Rossaint & Kreyenschmidt, 2015). Therefore, several actors in the food supply chain are familiar with the technologies and their use is being reconsidered in order to reduce the amount of waste. For the successful and efficient implementation of new monitoring tools, capturing the status quo about existing and established temperature monitoring and data exchanging systems along the chains is mandatory. Thus, this study aimed at the investigation of the status quo of temperature monitoring in food supply chains. Therefore, a comprehensive survey among different companies was conducted to determine the status quo of temperature monitoring and data management conditions, applied monitoring solutions as well as the establishment of novel, digital monitoring systems and their requirements. Secondly, three selected supply chains were investigated in practical studies. The applicability of the OnVu™ TTI using a novel app for the color read-out was tested as a temperature monitoring tool to identify weak points in the cold chains and to optimize cold chain management. The supply chains were a conventional B2C supply chain for raw-pork sausage, a B2B supply chain for fish and a B2C e-commerce for mixed products. Focus was laid on different requirements for the TTI as a temperature monitoring tool in different supply chains, i.e., the reflection of temperature conditions on a pallet and single unit packaging level, the reliable indication of temperature conditions on the box level and the application in boxes with mixed products.

3.3 Materials and methods

3.3.1 Experimental design

To investigate temperature control systems in cold food supply chains, two approaches were combined. In the first step, a comprehensive survey of German companies dealing with perishable food production, processing, logistics, wholesale, and retail was carried out to gather information regarding current temperature monitoring and data management conditions as well as the applied temperature monitoring systems, such as TTIs. In the second step, the applicability of the OnVu™ TTI combined with a novel app-based read-out system and cloud-based data collection as a tool for the temperature monitoring and identification of weak points in the cold chain was tested under real chain conditions in different supply chains. Three separate pilot studies were conducted in the B2C, B2B and B2C e-commerce sector, characterized by different supply chain properties. The first study was conducted in a classical B2C supply chain of raw pork sausage. The aim was to test the general applicability of TTIs and the app for the reproducible refection of temperature conditions on single unit packaging and pallet level as well as during storage. The second pilot study was conducted in a B2B supply chain of fish packed under modified atmosphere (MA). The objective was the implementation of TTIs in combination with the app as a reliable indicator of temperature conditions also at the secondary packaging level. The third study was conducted in a B2C e-commerce supply chain. The aim was to investigate TTIs and the app as a tool during the last mile for delivery services as well as for end customers. Here, the focus was laid on the challenge if temperature conditions can be adequately reflected by TTIs in boxes with mixed products under the influence of different goods, loadings, and initial temperatures.

3.3.2 Analysis of temperature monitoring and data management conditions in food supply chains – design of the survey

The survey was developed based on a comprehensive literature research, including scientific papers, regulations, legislations, and patent specifications. The questionnaire was created using the web-based application UmfrageOnline (enuvo GmbH, Pfäffikon SZ, Switzerland). German companies in the field of perishable food production, processing, logistics as well as wholesale and retail companies (including e-commerce) have been contacted by email including an individualized online link to the questionnaire. It consisted of 53 questions (50 mandatory questions, three questions with reply by choice in a text field), with 22 questions addressed to all participants and 31 questions addressed in dependence on the participant’s answer or affiliation. The survey was divided into four parts with the following content priorities:

1. Sector, related product categories and general information about the company
2. Transport, delivery, and cooling/refrigeration technologies

3. Temperature monitoring, control, and systems

4. Data collection and management

The first part included questions about the specific sector and product categories, which are produced, transported, or provided, as well as the size of the company and the commuting area. In the second part, transport processes, the frequency of delivered or received products, and applied cooling technologies were characterized. The third part evaluated challenges and weak points along the supply chain as well as temperature and quality control at the point of incoming and outgoing goods, its frequency and applied monitoring systems, such as contact thermometers, data loggers or smart technologies. The fourth part focused on the methods and technologies of product identification and traceability, data collection as well as a future conversion and application of digital systems. Ways of temperature data storage and exchange were identified. In total, 550 companies were approached based on online search and by using existing address lists of the participating academic institutions. The sample included in total 45 companies, who have answered the questionnaire, with n = 35 from the production/processing sector, n = 16 from the logistics sector, n = 14 wholesaler, n = 11 retailer, and n = 6 e-commerce (multiple answers were possible).

3.3.3 Investigation of different supply chains to analyze the application of the OnVu™ TTI with an app-based read-out system for the temperature monitoring

3.3.3.1 Charging of the OnVu™ TTI and measuring by app and colorimeter

For all pilot studies, the well-investigated OnVu™ TTI (Ciba Specialty Chemicals & Freshpoint, Basel, Switzerland, patent WO/2006/048412, Batch 21.06.2021, Color Batch 00552HN8) was used. The pigmented water ink in the center of the label is activated by a UV light charger (GLP 80/56 TTI, Bizerba, Germany) and automatically equipped with a protective UV filter (LOT# 000018272) by thermal transfer print at ambient temperatures of 3°C–5°C. The color of the label changes from blue to white dependent on time and temperature conditions (Kreyenschmidt et al., 2010). The amount of UV light can be individually set with the duration of illumination in milliseconds (ms) to determine the initial color of the label and the length of the discoloration. Labels were attached to the packages at defined positions with two underlying layers of self-adhesive white paper to ensure a consistent background for color measurements. Each label included a printed QR code, enabling a serialized product attribution to measured TTI values after scanning.

The color measurement app used to read out the labels is described by Waldhans et al. (2023). It works for Android operating systems. While taking a picture of the TTI, color values of the blue dot in the center of the label and color values of the surrounding white points were automatically measured to calculate the TTI values including a white balancing to eliminate environmental influences. Color values were saved as CSV files on the smartphone. App measurements were conducted using two Android smartphones, Nokia 7.2 Dual-SIM Android™ 9.0 48 m pixels (Nokia Oyj, Espoo, Finland) and HUAWEI P30 lite Dual-SIM Android™ 9.0 48 m pixels (Huawei Technologies Co., Ltd, Shenzhen, China). Measurements apart from the laboratory were conducted free-handed, measurements in the laboratory in a darkroom with a fixed holder for the smartphones, each with a 2x zoom in an appropriate distance horizontally to the TTI. A daylight lamp (1620Lm, 6500 K, Tageslichtlampen24.de, Kiel, Germany) was used for sufficient light conditions in both settings. Color measurements were in parallel conducted by colorimeter as reference using EyeOne i1 Basic Pro1 and the software KeyWizard v2.50 (X-rite; Gretag Macbeth, Regensdorf, Switzerland). In all pilot studies, samples/packaging units were stored after transport in the laboratory for further investigations in high-precision low temperature incubators (MIR 153, SANYO Electric Co., Ora-Gun, Gumma, Japan). Temperature was monitored by data loggers (Testo SE & Co. KGaA, Titisee-Neustadt, Germany).

3.3.3.2 Pilot study in a B2C raw pork sausage supply chain

The first practical trial was conducted in a German supply chain for raw pork sausage to test the general applicability of the OnVu™ TTI and the measurement app for the reproducible reflection of temperature conditions on a product and pallet level. Two pallets, containing each 113 (pallet 1) and 262 (pallet 2) single unit packages of MA packed raw pork sausages (750 g per package, 5 sausages with each 150 g), were monitored. The temperature limit for the product was 4°C. The study was performed during the summer season as this is the main season for the demand of raw pork sausages and a critical time for cold chain interruptions. TTI labels were charged (1500 ms) and fixed on each single unit packaging immediately after production. Single unit packages were packed in open cardboard boxes, each containing four packages. Eight cardboard boxes were arranged on each pallet layer, resulting in 3.5 pallet layers for pallet 1

(Figure 3.1a) and eight layers for pallet 2. On pallet 1, data loggers (iButton DS1922L Thermochron Data Logger, Maxim Integrated, San Jose, CA, USA) were positioned at four different positions on the pallet (top and bottom layers) to monitor the temperature conditions during storage, commissioning and transport every 5 min.

After storage and commissioning at the producer, the pallets were distributed to the factory sale in an actively cooled truck. Pallet 1 was unloaded and single packages were either stored in the cold storage room or in the display. Temperature conditions in the cold storage room were furthermore measured by the attached loggers, where packages in the cardboard boxes were redistributed. Temperature in the display was likewise measured by data loggers (Testo SE & Co. KGaA, Titisee-Neustadt, Germany) every 5 min. Pallet 2 was further transported to the laboratory, where packages were stored at four different constant temperature conditions (2°C, 4°C, 7°C, 10°C). All TTIs were measured by app and colorimeter at the initial charging point (t=0 h). TTIs on pallet 1 were in addition measured upon arrival at the factory sale (t=15 h), after storage in the cold storage room and in the display (t=22 h). TTIs on pallet 2 were in addition measured upon arrival at the laboratory (t=48 h) and at defined investigations points dependent on the storage temperature.

3.3.3.3 Pilot study in a B2B fish supply chain

The applicability of the OnVu™ TTI and the measurement app at the box level as secondary packaging was investigated in a B2B fish supply chain in the second scenario. Three expanded polystyrene (EPS) boxes (λ=0.035 W/mK [41], 395 x 295 x 190 mm, thickness: 15 mm at walls and bottom, 12 mm at lid), each containing two packages of MA-packed gilthead seabream (*Sparus aurata*) with 2–3 fishes à 300–400 g per package (total weight per box 1.8–2.1 kg) were monitored. The field study was conducted during the winter season. TTIs were charged (500 ms) at a logistics platform. Each box was equipped with 19 TTI labels at different positions inside and outside the box as well as on the fish packages (Figure 3.1b): Two labels on each outside, two labels on two insides each, two labels on the inside of the lid, four labels on the top of the upper packaging, and one label on the side of the upper packaging. As coolant, frozen gel cooling packs were positioned on the upper packaging. The polystyrene boxes were perforated at the bottom to enable draining of melt water. The boxes were equipped with temperature loggers (iButton DS1922L Thermochron Data Logger, Maxim Integrated, San Jose, CA, USA) at five different positions (long and short outside and inside, lid, upper side of the packaging) near the attached TTIs, monitoring the temperature during transport and storage every 5 min.

Prepared boxes were positioned on a pallet with other perishable goods at different points (bottom, middle and top layer). Boxes were distributed from the logistics platform to the wholesale market in an actively cooled transporter within 24 h. An onward transport of the boxes to the laboratory at the University of Bonn was performed at ambient temperature conditions, simulating real temperature fluctuations occurring during customer transports. Boxes were then stored for 4 h at 4°C and afterward for 20 h at 2°C to simulate storage conditions at the customer, i.e., catering and gastronomy. Color measurements by app and colorimeter were conducted at defined inspection points in the chain: at the initial charging point (t=0 h), at the factory sale (t=20 h), after arrival at the laboratory (t=23 h), after storage at 4°C (t=27 h), and after storage at 2°C (t=48 h).

3.3.3.4 Pilot study in a B2C e-commerce supply chain

The third supply chain is a B2C e-commerce for perishable and non-perishable food products with the aim to test TTI and app for the temperature monitoring in mixed boxes during the last mile. Sixty-four boxes with mixed perishable and non-perishable products were delivered from an e-commerce retailer to the customer in passively cooled boxes within 24 h of transport. The cardboard boxes used for transport (400 x 330 x 280 mm) were isolated with inserts made of pressed straw (λ=0.041 W/mK, thickness: 35 mm at walls, bottom and lid) wrapped with polyethylene foil. The volume of the box’s interior is 18 l. As coolant, plastic bottles (0.5 l) with frozen water were used according to the company’s specification. The field test was conducted in winter as this is the main season for orders. TTI labels were activated (450 ms) in the cooling room at the online retailer. One TTI label per box was fixed on a strap, the second TTI label was fixed on an inlay. The strap could be pulled out from the outside of the box to read-out the label without opening. 58 boxes for customers and six test boxes for the University of Bonn were packed with ordered goods, coolants and filling material according to the packing scheme of the company. Every box contained vacuum packed galeeny breast (ca. 600–700 g) as a reference product with a temperature limit of max 4°C. When packing, strap and inlay were positioned in the center of the box close to the reference product, with no direct contact to the coolant (Figure 3.1c). Ten customer boxes and six test boxes were equipped with temperature loggers (iButton DS1922L Thermochron Data Logger, Maxim Integrated, San Jose, CA, USA) fixed on the inlay, two test boxes were in addition equipped with data loggers outside to monitor the temperature every 5 min. Customer and test boxes were shipped in a transporter under ambient temperature conditions. Test boxes were stored at the laboratory for another 28 h. Boxes were stored at three different temperature scenarios (two boxes each): a constant scenario (28 h at 20°C), a dynamic winter scenario according to a part of the AFNOR Standard 48 d (11 h at 5°C, 9 h at 9°C, 2 h at -2°C, 6 h at 5°C) and a dynamic summer scenario according to a part of the AFNOR Standard 48 b (4 h at 25°C, 4 h at 32°C, 3 h at 25°C, 9 h at 20°C, 8 h at 25°C). TTI color values were measured by app and colorimeter at three investigation points: all TTIs immediately after charging (0 h), test boxes at the arrival in the laboratory (20 h) and after storage at the different scenarios (48 h). The app was also made available to customers via QR Code. Customers were equipped with a guide to download, install and use the app. The customer was instructed to take proper pictures of the TTI by app immediately after opening the box under sufficient light conditions without shadows or surrounding borders. Color values measured by customers were automatically saved in a cloud database when taking the pictures.

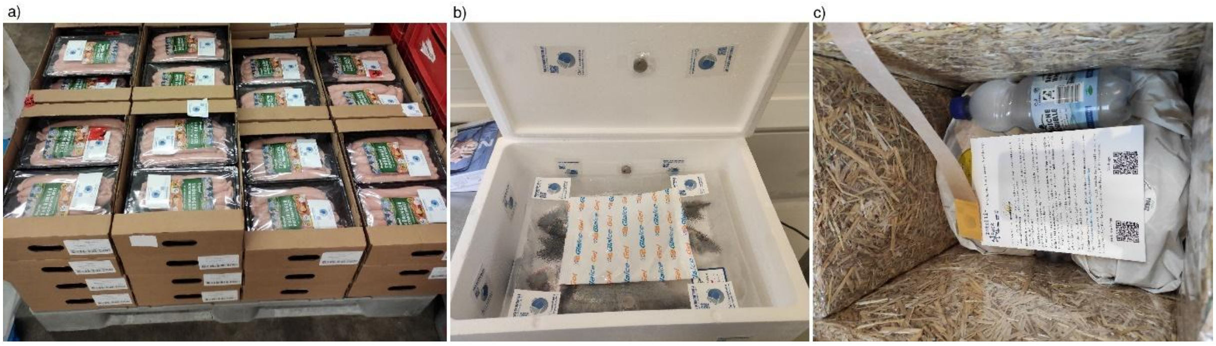


Figure 3.1. (a) Packages of raw pork sausages with TTIs and temperature loggers on pallet 1. (b) Fish box with TTIs and temperature loggers at different positions. (c) Customer box with positioned TTI strap, inlay, packed products and coolant

3.3.4 Data analysis

Square values of the color values measured by app and colorimeter were calculated to describe the discoloration of the TTI and to compare results for app and colorimeter measurements. For app measurements, the medians of the gathered single R, G and B values for the blue dot (R_b; G_b; B_b) and the white color point (R_w; G_w; B_w) were calculated. Color values were corrected by white balancing color data for the blue dot, and then expressed as square values SV_{RcGcBc} as described by Waldhans et al. (2023).

$$R_c = (255 - R_w) + R_b \; ; \; G_c = (255 - G_w) + G_b \; ; \; B_c = (255 - B_w) + B_b \qquad (3.1)$$

where R_c; G_c; B_c: corrected color values by white balance; 255: absolute white; R_w; G_w; B_w: raw values for the white color points, R_b; G_b; B_b: raw values for the blue dot.

The square value SV_{RcGcBc} was then calculated with the corrected RGB color values.

$$SV_{R_cG_cB_c} = \sqrt{{R_c}^2 + {G_c}^2 + {B_c}^2} \tag{3.2}$$

The square value SV_{LAB} based on the measurements by colorimeter was calculated according to Kreyenschmidt et al. (2010).

$$SV_{LAB} = \sqrt{L^2 + a^2 + b^2} \tag{3.3}$$

where *SV*: square value; *L*: lightness/luminance; *a*: red and green component; *b*: yellow and blue component of the color.

Calculations and figures concerning the survey were performed using Microsoft Excel 365 (Redmond, Washington, USA). Further calculations and figures were made using the program software OriginPro 8.0G (OriginLab Corp., Northampton, MA, USA).

3.4 Results and discussion

3.4.1 Analysis of temperature monitoring and data management conditions in food supply chains – results of the survey

Most of the survey participants are dealing in the sector of production, transportation, and trading of perishable goods, i.e., dairy and meat products. The distribution between micro, small, middle and large-scale enterprises is balanced, with 20–29 % of each companies, providing a good representation of the corporate landscape dealing with supply chains of food products. 96 % of the companies are based in Germany and more than 70 % are mainly operating in Germany and neighboring countries. For transport, trucks with active cooling are used by most of the participants from the logistics sector (75 %, n = 12) and production/processing/trade sector (72 %, n = 31). As cooling techniques, mainly mechanical cooling units (71 %) and insulating boxes/containers (38 %) are used, assuming that it depends on the sector and the product category. The frequency of goods delivery and reception is in most cases several times a day, with 66 % and 52 %, respectively. The main challenges and weak points of the cold chain are revealed as temperature fluctuations in transport vehicles (60 %), loading processes (58 %) and storage in private refrigerators (42 %). Temperature and quality control methods of incoming and outgoing goods are shown in Figure 3.2a. Incoming goods are mainly controlled by visual inspection (64 %), the best-before-/use-by-date, measurement of the product surface temperature (each 60 %) as well as the temperature recorder of the delivery vehicle and the labeling (each 53 %). The control of outgoing goods is primarily conducted by ambient temperature measurement (67 %), visual inspection (64 %) and control of the best-before-/use-by-date (51 %). Thus, often only a visual inspection or the control of static conditions is carried out. Other inspections, e.g., detailed sensory inspection, are often time consuming. More than 60 % of respondents indicated that every delivery of incoming or outgoing goods is checked. However, it can be assumed that controls are randomized. This current state underlines the added value of TTIs as a measuring instrument at the individual product level. The results are partly similar to the results of Raab et al. (2008), which also revealed that product and ambient temperature and control of the best-before date are one of the most frequently used methods in incoming inspection in pork and poultry chains.

As temperature monitoring systems, non-contact thermometers (69 %), electronic data loggers (62 %), and contact thermometers (49 %) are mainly applied at different steps along the chain (Figure 3.2b). The use of data loggers during transport and storage is also shown by Raab et al. (2008) and is predicted to rise due the possibilities of integrating monitored data into cloud technologies (Hofmann & Mathauer, 2018). TTIs are only used by one company (2 %). In addition, the use of wireless technologies with integrated temperature sensors, e.g., RFID, is negligible, and Smart Active Labels are not used at all by the participants. Furthermore, 87 % pointed out not to plan replacing existing systems with new technologies, indicating that companies rely primarily on classical methods to carry out only the obligatory temperature controls. Most of the companies (87 %) are generally using paper documentation (delivery notes) for product identification and traceability. The manual capture of printed product data and 1D barcodes are used by 31 % and 29 %, respectively. 2D/3D-Codes or RFID technologies are hardly or never used (0–7 %). A low use of sensor technologies in the meat supply chain was also shown by Ersoy et al. (2022).

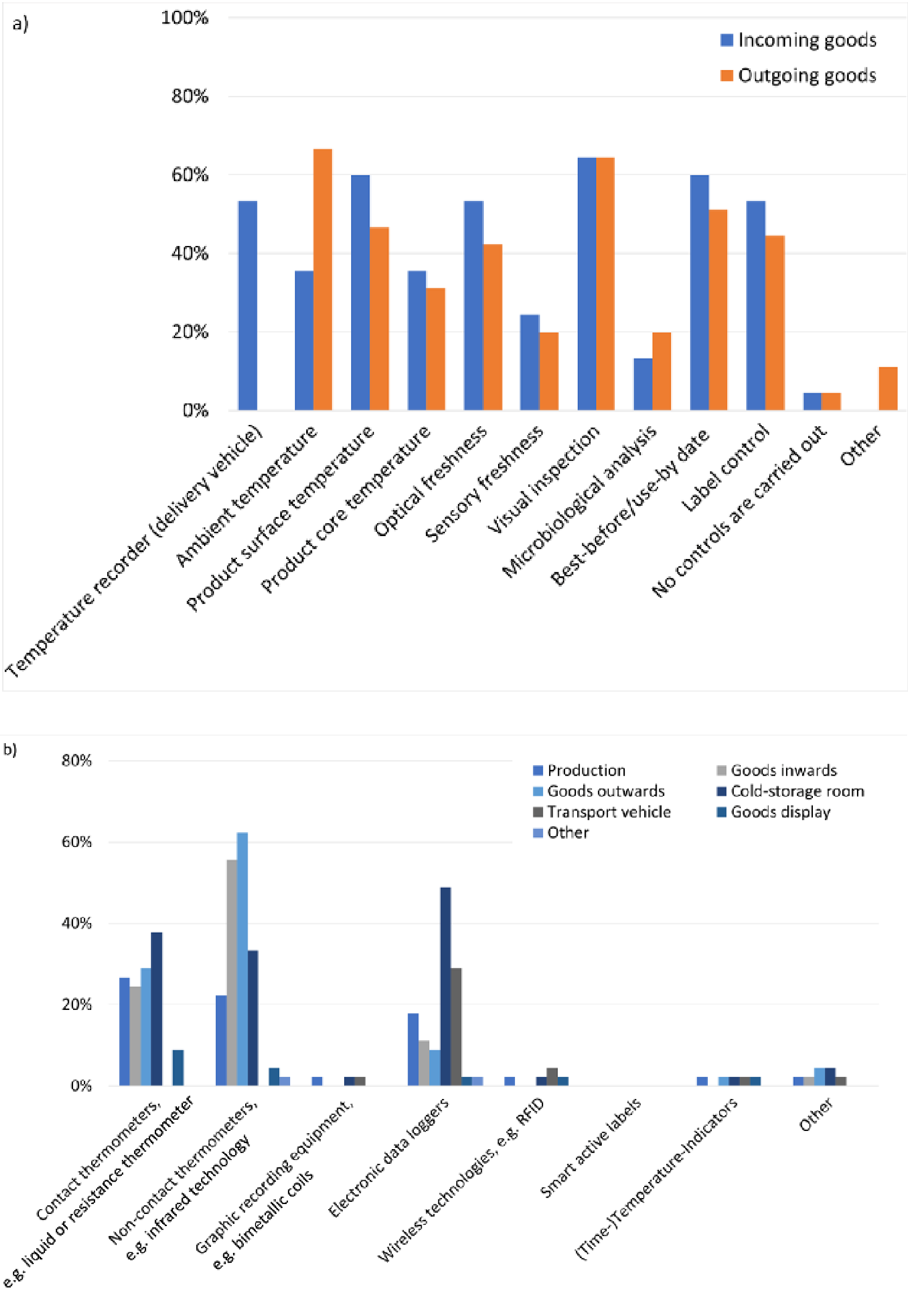
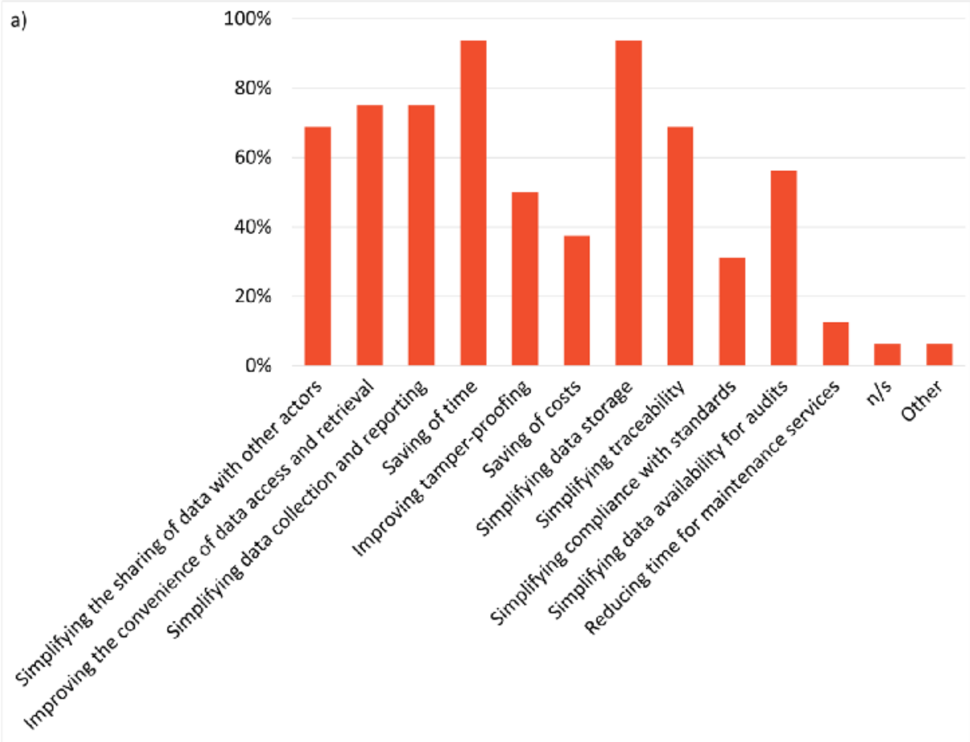


Figure 3.2. (a) Type of temperature conditions, quality parameter or other inspection that are controlled at the point of incoming and outgoing of perishable products (n=45). (b) Usage of different temperature monitoring systems at different steps of the supply chain (n=45). (Multiple mentioning was possible)

Our survey revealed that temperature data is recorded either only digitally by 4 %, only in written form by 24 % or both digitally and in written form by 64 %. 40 % of the participants using partly or completely written documentation plan to switch their temperature monitoring to digital documentation. The main reasons are saving of time and simplifying data storage (each 94 %), shown in Figure 3.3a. Focus is also laid on simplification of processes, as data access and retrieval, collection and reporting as well as data sharing and traceability (69–75 %). However, other participants (40 %) are satisfied with the current system of written documentation. Stakeholder awareness is therefore needed to demonstrate the facilitation for controls through digital systems. Currently, digital temperature data in the companies are mainly stored on in-house/on-premise servers (33 %), whereas cloud systems are negligible used or participants did not answer. Ersoy et al. (2022) showed partly different results, revealing that in meat supply chains in Turkey, data mining and cloud computing are used for information sharing. 32 % of the participants exchange temperature monitoring data with stakeholders by written transfer, 40 % only on request or reclamation and only 2–9 % use digital tracking or transmission at the point of incoming goods as well as share data in a cloud (Figure 3.3b), which reveals overall low transparency along the chain.

The results showed that developments in data exchange have not substantially progressed in the last decade, which becomes clear by the fact that Raab et al. (2008) already showed a data exchange of less than 50 % between actors in pork and poultry chains and paper documentation as the most applied form of temperature inspection. The sharing of supply chain data is not only revealed both as highly valuable but also of highly sensitive concern (Qian et al., 2022). This is also shown by the fact that some questions were not replied in this study. However, the results indicated that stakeholders are generally willing to share temperature and other information, also shown by the studies of Hsiao & Huang (2016) and Minnens et al. (2019). Moreover, there is a change compared to previous decades, as the current developments in digitization play a decisive role in driving forward the data collection and exchange, complemented by the availability of a large amount of data (Kiil et al., 2019). The digitization brings with it new challenges, such as varying IT application systems and IT structures amongst stakeholders (Ersoy et al., 2022; Mercier et al., 2017). Furthermore, especially small and medium-sized enterprises are still skeptical concerning the benefits for their organizational structure, also because resources and financial opportunities are rare (Donnelly et al., 2013; Jonkman et al., 2022; O’Connor & Kelly, 2017; Rejeb et al., 2022). Based on the survey results, it can be assumed that stakeholders only implement the obligatory legal requirements on temperature monitoring and an investment in digital systems is not seen as an added value. This is supported by the fact that mainly classical temperature monitoring methods are used, even though there are many developments in the field of TTIs and other innovative technologies. However, the upcoming digital data exchange solutions could provide also new possibilities for the implementation of TTI systems, enabling data transmission and therefore eliminating disadvantages compared to more expensive RFID systems (Zuo et al., 2022).



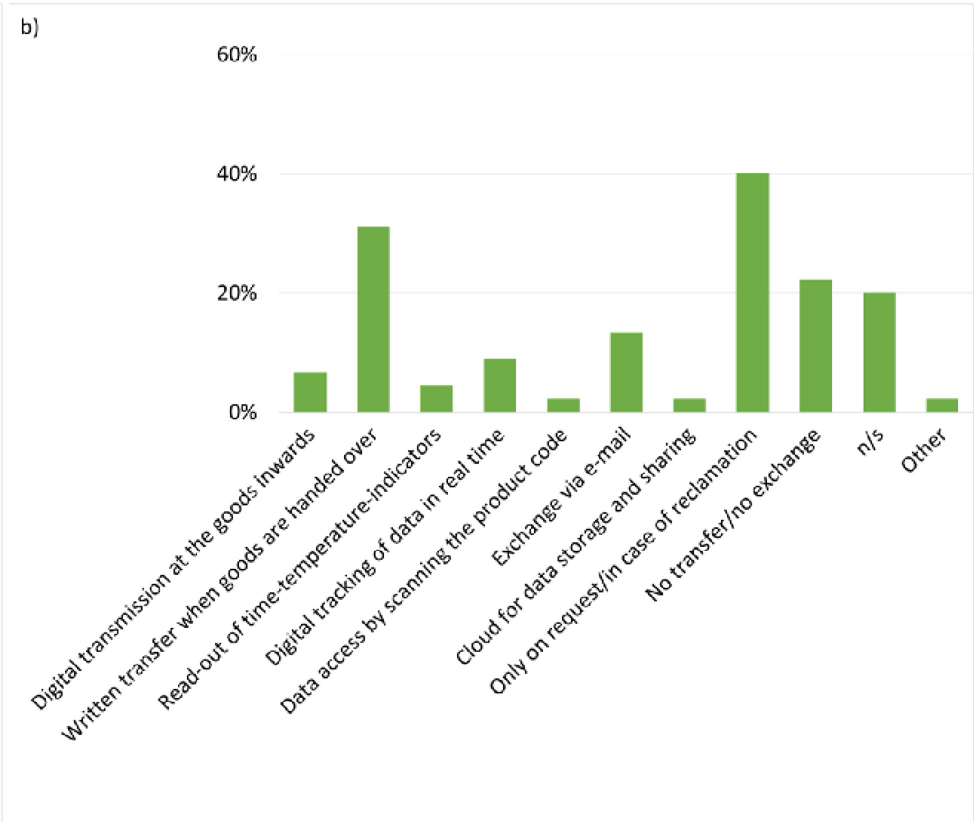


Figure 3.3. (a) Reasons for switching to digital recording of temperature data (n=16). (b) Methods of temperature data exchange with associated supply chain actors along the chain (n=45). (Multiple mentioning was possible)

3.4.2 Application of the OnVu™ TTI and an app-based read-out system for the temperature monitoring in different supply chains

3.4.2.1 Pilot study in a B2C pork meat supply chain

Temperature conditions during transport of pallet 1 and storage of samples in the factory sale are shown in Figure 3.4. The mean temperatures on different pallet levels during commissioning and transport time were between 4.3 ± 0.9°C (Bottom pallet layer 2) and 5.0 ± 0.6°C (Bottom pallet layer 1). In the cold storage room and the sales display, mean temperatures of 4.2°C ± 0.7 and 4.5°C ± 0.6, respectively, were measured, revealing that temperatures during transport and storage were generally stable. Variances of up to 6.3°C between pallet levels during transport and slight fluctuations during storage were caused by the exposure to cooling units and doors, as also shown by Raab et al. (2008). Mean temperatures were slightly above the threshold temperature (4°C) which might be caused by the high ambient temperatures in summer. However, the variances were minor in contrast to other studies revealing temperature fluctuations of up to 19°C during transport and at the retailer (Giannakourou et al., 2005; Nunes et al., 2009; W. Zeng et al., 2014). Despite high temperature differences on pallet levels during commissioning and storage, temperature conditions compensated each other (Figure 3.4). TTI measurements by app (Nokia) after transport also revealed similar results on pallet levels from SV_{RcGcBc} 240.2 ± 14.28 to 243.32 ± 16.84 (Figure 3.5) with comparable results for measurements by Huawei (data not shown), revealing that the app can reliably reflect the temperature conditions.

Reference measurements by colorimeter confirmed the low variances during transport (SV_{LAB} 58.1 ± 0.39 to 58.5 ± 0.46, Figure 3.5). The range of standard deviations (SD) for app measurements was comparable to colorimeter measurements, as already shown by Kreyenschmidt et al. (2010), which revealed a high reproducibility also achieved by the app. The stable temperature conditions during storage in the factory sale further revealed no remarkable or even lower discoloration of TTIs measured by app, whereas measurements by colorimeter showed a slightly increased discoloration (Figure 3.5). This might be caused by a lower color sensitivity of the smartphone and the influence of environmental conditions as light exposure or shadows in the sales room

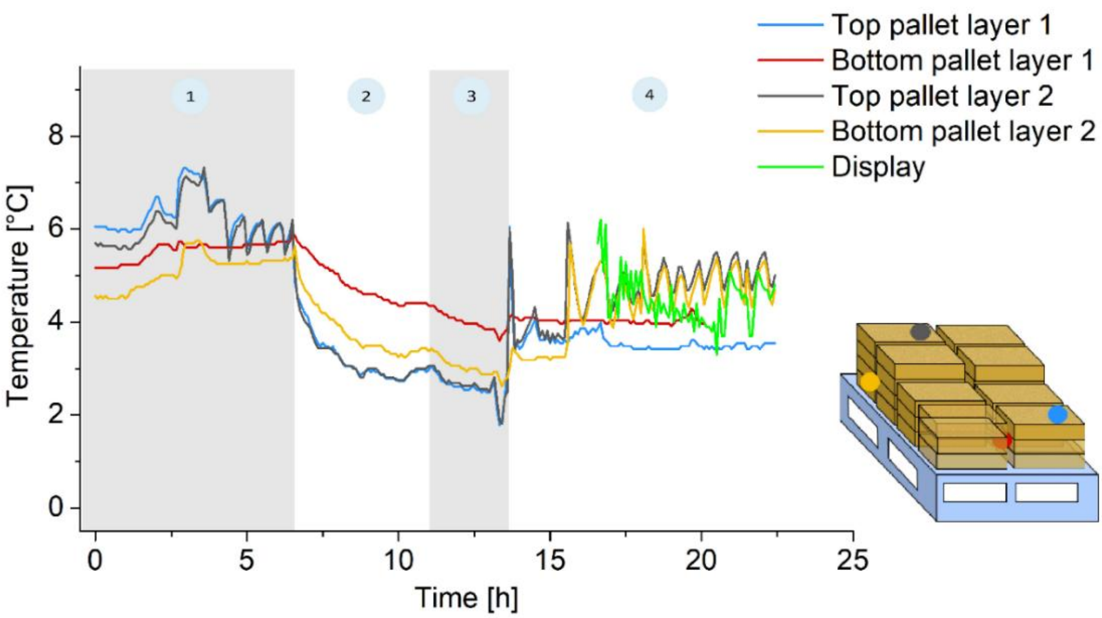


Figure 3.4. Temperature conditions on pallet 1 during transport to factory sale and storage. 1. Storage and commissioning at the production, 2. Transport, 3. Arrival and stay in the truck, 4. Storage at the factory sale's cold storage room and sales display

Even if the cold chain in this study was generally well-maintained, slight fluctuations during transport and storage as described above implied the potential weak points in the chain during transport and loading processes caused by the position of the cooling unit, the airflow and varying initial product temperatures (do Nascimento Nunes et al., 2014; Mercier et al., 2017; Nychas et al., 2008), which need an accurate monitoring. To evaluate if app measurements of TTIs could also reflect temperature abuses at weak points, they were in addition tested at different temperature scenarios in the laboratory. Differences in TTI color values at varying temperatures measured by app and colorimeter are exemplary shown for 4°C and 10°C in Figure 3.6. The enhanced TTI discoloration at the higher storage temperature of 10°C could reliably be reflected by app measurements, showing remarkably higher values at each time point than at 4°C. Results were confirmed by colorimeter measurements. SDs were likewise low for both measuring methods. The application of TTIs as a valuable tool for temperature monitoring and detection of temperature abuses in perishable supply chains is well-known for years (Taoukis & Labuza, 1989; Tsironi et al., 2008), and TTI app measurements now offer a promising new tool for the detection of weak points along the chain.

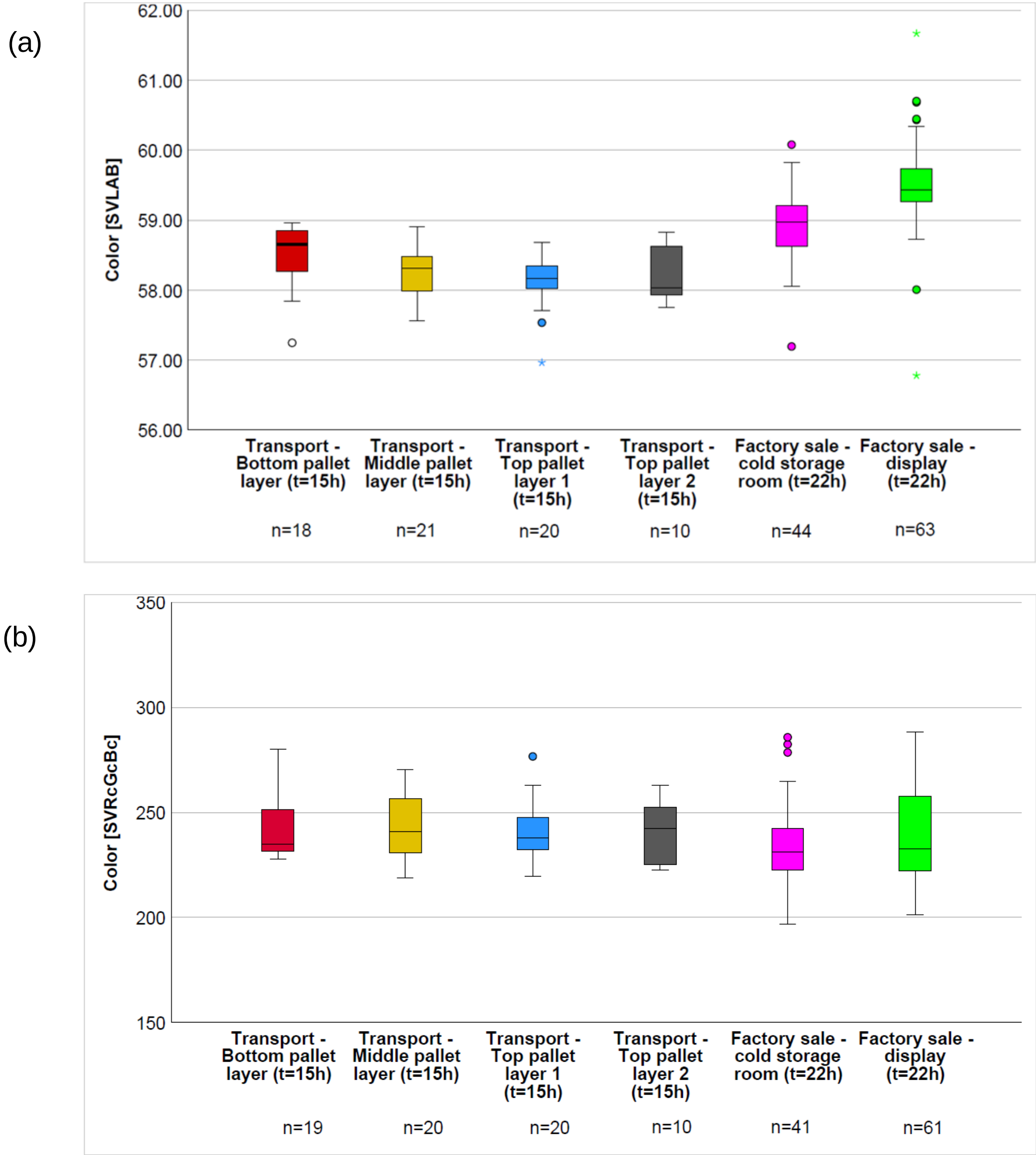


Figure 3.5. Boxplots showing the color of TTIs at different positions on the pallet after transport and after storage at different areas the factory sale, measured by (a) colorimeter and (b) app. Dots reflect mild outliers. Stars reflect extreme outliers

The simple procedure of the app measurement shows the general high feasibility of this method and further simplifies the easy-to-use response of a TTI based on its color (Gao et al., 2020). Furthermore, reliable and objective app measurements overcome the existing hurdles concerning applicability of TTI use in practice (Taoukis, 2001). Especially for the inspection of incoming goods and temperature controls several times a day, app measurements represent an alternative to existing, less reliable controls, such as the visual inspection or truck temperatures. The use of data concerning detected weak points combined with digitalized traceability systems of the stakeholders can optimize the cold chain management in the long term. In further combination with shelf life models for the product, temperature monitoring with TTIs can be extended by the calculation of a dynamic shelf life based on actual temperature data (Albrecht et al., 2020; Corradini, 2018). This enables not only a helpful tool for all stakeholders including the consumer but also offers discounting strategies to reduce food waste and improve sustainability along the chain (Buisman et al., 2019; Heising et al., 2017; Poyatos-Racionero et al., 2018).

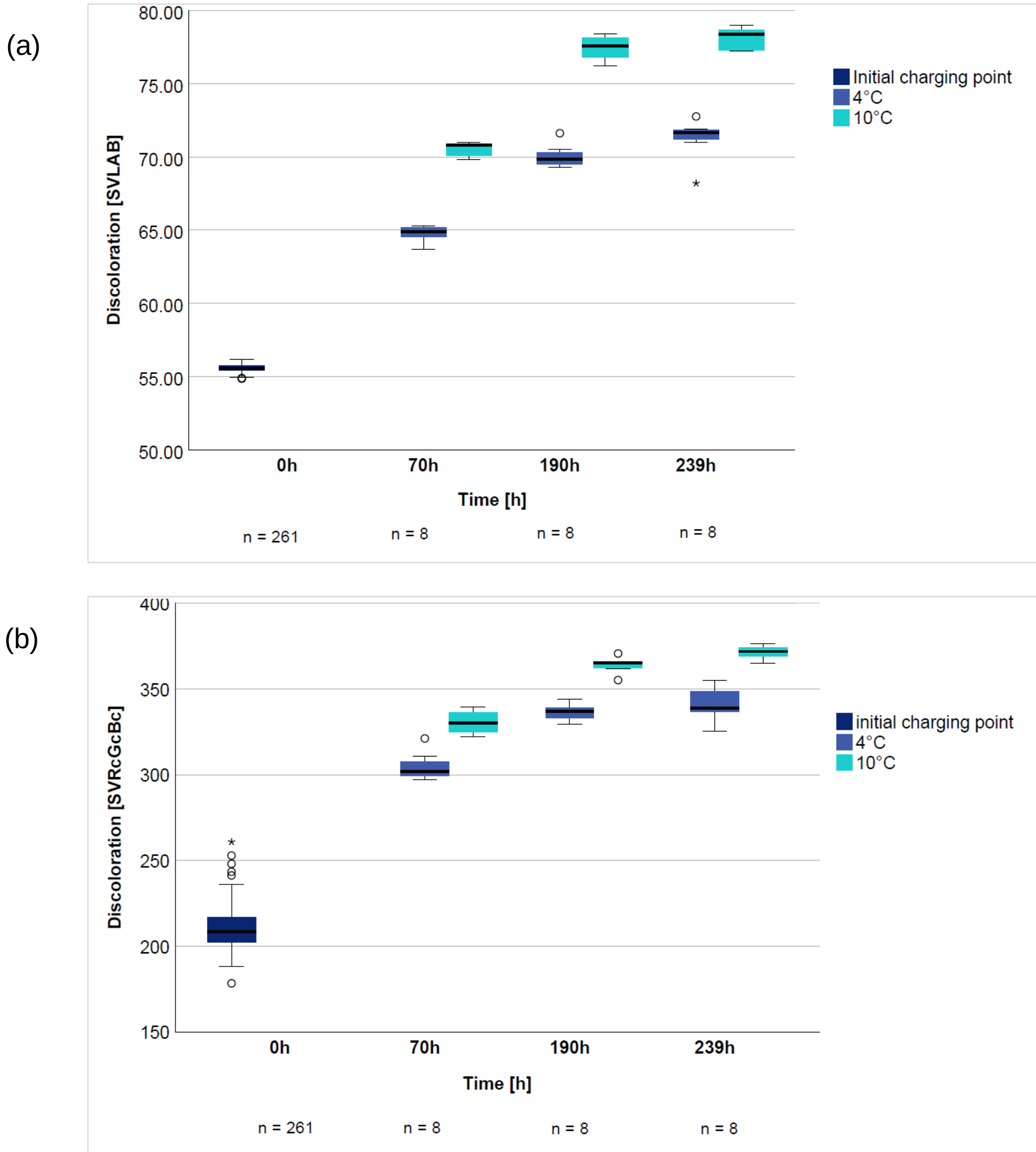


Figure 3.6. Boxplots showing the TTI color at the initial charging point and discoloration of TTIs during storage at 4°C and 10°C at the laboratory at selected time points, measured by (a) colorimeter and (b) app. Dots reflect mild outliers. Stars reflect extreme outliers

3.4.2.2 Temperature monitoring in a B2B fish supply chain

Temperature conditions during transport and storage in the B2B chain are shown in Figure 3.7, exemplary for box 1. Temperatures at the outside of the boxes increased at the warehouse for 5 h with a maximum value of 10.4°C and a mean temperature of 6.9°C ± 3.6, suggesting that the boxes were temporarily stored unchilled, e.g., at a walk-through room or loading area. Loading and unloading areas are critical points for temperature abuses, also shown by the survey results as well as by Raab et al. (2008) and McKellar et al. (2014).

Martinsdottir et al. (2010) and Lundén et al. (2014) showed strong temperatures abuses in fish supply chains at arrival points, too. The unchilled storage also caused temperatures above the threshold of 2°C inside the box, however, temperatures were significantly lower compared to the box outside with a maximum value of 7.1°C and a mean temperature of 4.8°C ± 1.9. It was shown that the temperatures at box outsides did not reflect the real conditions inside the box, as they had been too strongly influenced by temperature interruptions and high fluctuations. Consequently, also TTIs attached outside resulted in a significantly higher discoloration. Even though they are easier to attach and handle (Jedermann et al., 2014), the box outsides were not further considered as a reliable placement of TTIs. Temperatures inside the boxes at different positions are in a similar range during the entire storage time, revealing 3.1°C ± 2.4 (product) to 3.3°C ± 2.5 (long side) in box 1 and similar results for the other boxes. Lid and long inner side were slightly more sensitive to temperature interruptions and fluctuations than the product, showing higher increases at the time points regarded (Figure 3.7). Giannakourou et al. (2005) showed comparable results for temperature conditions in boxes with gilthead seabream, indicating that the warmest point was the top of the box and coldest temperatures were in the center near the product and ice coolants.

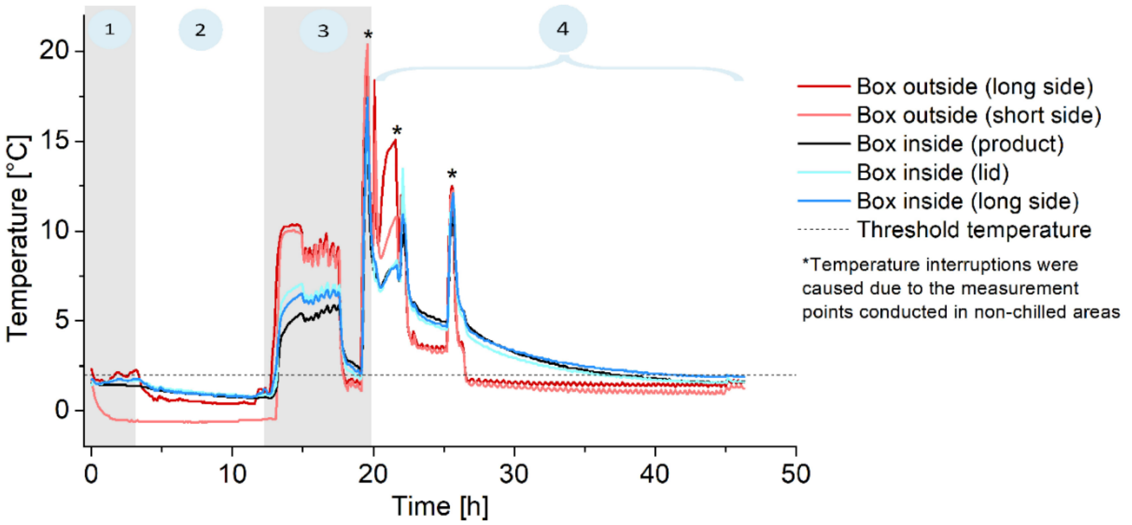


Figure 3.7. Temperature conditions outside and inside of box 1 during transport and storage. 1. Commissioning, 2. Transport, 3. Arrival and storage at the warehouse, 4. Transport, storage and measurements at the laboratory

Results for the discoloration of TTIs by colorimeter measurement showed similar behavior for the different positions inside the box, revealing the highest discoloration at the lid position in box 1 (Figure 3.8a). Comparable results were shown for box 2 and 3. App measurements showed partly differing tendencies with no visible trend regarding the positions, mainly caused by environmental light influences on the app measurements, also shown by the high SDs (Figure 3.8b). However, the study shows that it is generally possible to monitor the temperature conditions inside the box via TTI also at the general box level instead of the product level. The results of Giannakourou et al. (2005) showed similar observations when comparing TTI responses with temperature data during the ice-cooled transport of gilthead seabream. To avoid inaccuracies at lid and inner side, the application of a TTI inlay close to the product should be considered to monitor product temperature as accurate as possible. Moreover, this would also facilitate the measurement process, since the study revealed that the read-out on the inside of the box is challenging.

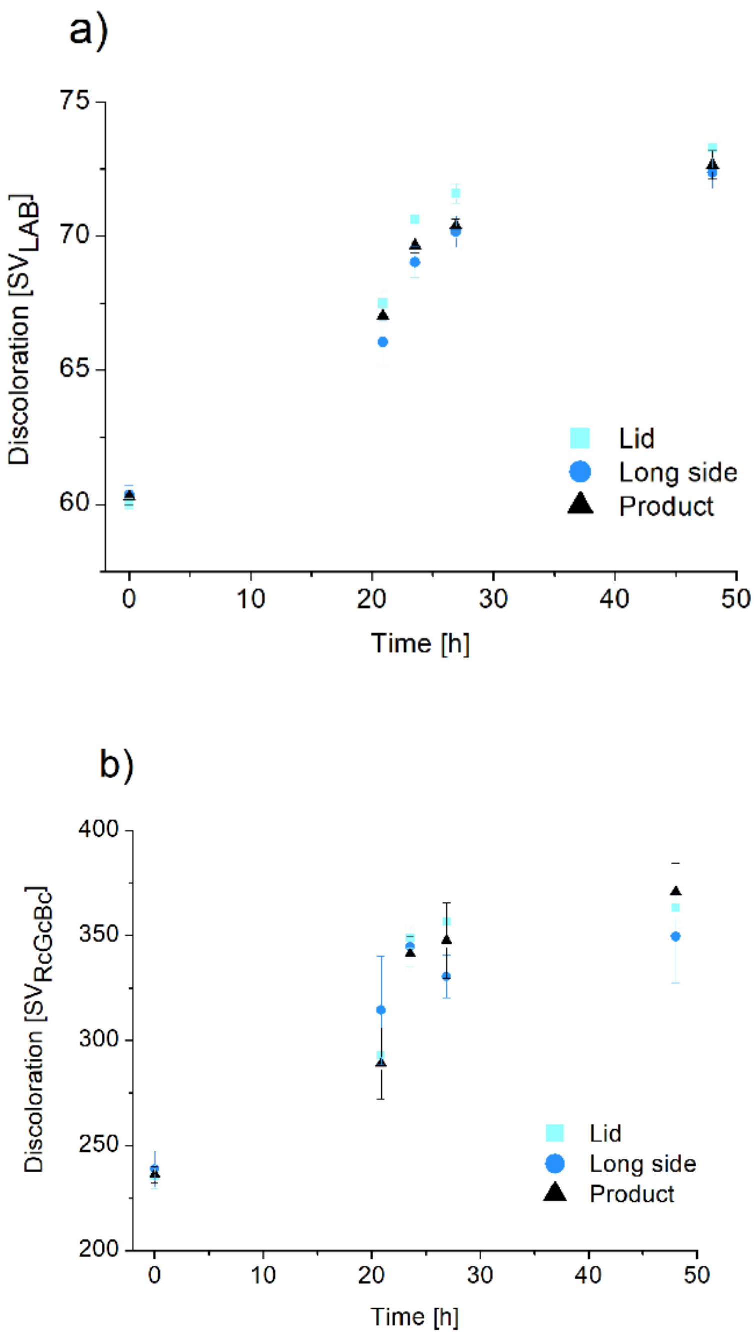


Figure 3.8. Discoloration of the TTI at different positions (Lid: n=2, Long side: n=4, Product: n=5) inside box 1 during transport and storage, measured by (a) colorimeter and (b) app

Knowledge about the temperature conditions along the B2B chain, and the digital read-out by app, whose data can also be stored and shared online, can help to detect temperature abuses before goods are reaching the consumers and to optimize logistic processes. The integration of the QR code into the OnVu™ TTI label for a direct serialized data transfer on product or box level is a valuable and cost-effective addition for the seafood sector (Ahamed et al., 2020; Sahin et al., 2023). A link with other traceability platforms providing additional supply chain information such as described by Oliveira et al. (2021) can offer an added value. However, it must be considered that exchanging sensitive data along B2B chains is dependent on multiple factors, such as the interaction and power of actors, the willingness to share data and the uncertainty of product quality (Hsiao & Huang, 2016; Kumar Mangla et al., 2021). Efforts at persuasion are needed at different stages to successfully implement a temperature monitoring system.

3.4.2.3 Temperature monitoring in a B2C e-commerce supply chain

Temperature conditions in customer and tests boxes during transport are shown in Figure 3.9. Firstly, it must be mentioned that only five of ten temperature loggers dispatched with the customer boxes were returned. A return of less than 50 % of the loggers by customers was also shown in the studies of Derens-Bertheau et al. (2015) and Gogou et al. (2015). A more comprehensive data monitoring at the customer level in the future would be more revealing. Mean temperatures during transport ranged from 2.0°C ± 1.3 (test box 1) to 4.6°C ± 1.1 (test box 4) within the boxes. Thus, the cold chain in all boxes was generally well-maintained, showing a consistent decrease in temperature and no interruptions. However, the temperatures decreased variously and the threshold temperature of 4°C was reached in a range of 0.5 to 11.9 h, leading to temperatures at the point of delivery from 1.0 to 3.4°C. Temperature differences were caused by various packaging units, product loadings and initial product temperatures, demonstrating the need for an adequate temperature monitoring in mixed boxes as well as a proper cooling of the goods before delivery. TTIs on inlays could well reflect temperature conditions in the boxes, as color values mainly showed the same trend: Test box 4 showed the highest discoloration after 20 h with SV_{RcGcBc} 335.52 measured by app and SV_{LAB} 66.58 measured by colorimeter (Figure 3.10a and 3.10b). The lowest mean temperature of test box 1 is reflected by lower measured color values of SV_{RcGcBc} 306.35 and SV_{LAB} 63.29, respectively. Discoloration trends measured by app were highly comparable regarding both smartphone measurements. TTIs positioned on the strap could not exactly reflect the trend of varying mean temperatures. It must be considered that a slipping out of position during transport may have occurred and that temperature loggers were positioned closer to the inlays, resulting in more reliable results for the inlays.

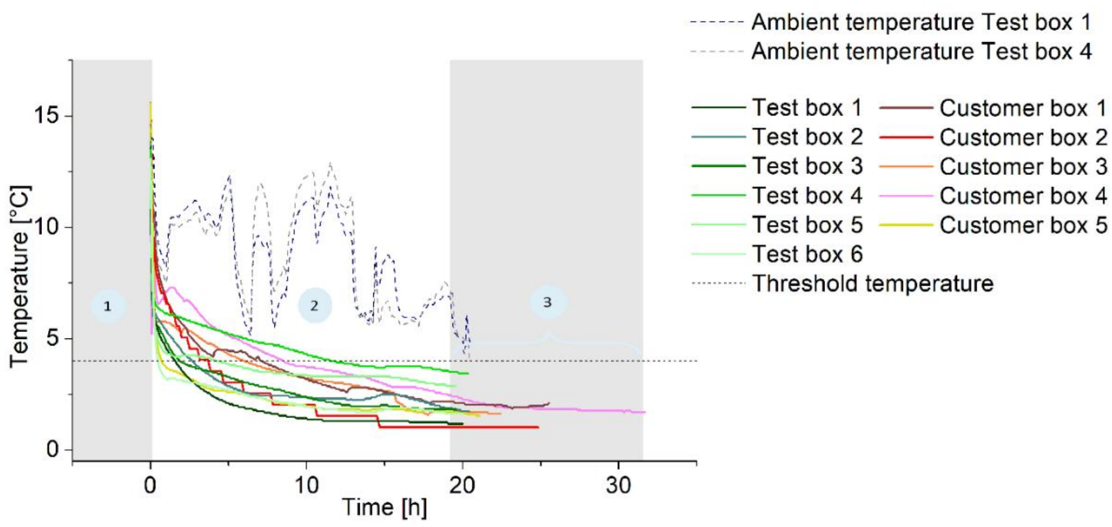


Figure 3.9. Temperature conditions within the customer's and test boxes during transport. 1. Packing of the boxes, 2. Transport, 3. Arrival times/Opening of the boxes

TTIs on the inlays could also well reflect the temperature conditions within the mixed boxes during storage at the different temperature scenarios in the laboratory, showing results of SV_{RcGcBc} 358.60–357.92 for 20°C scenario, 336.10–340.44 for winter scenario and 366.69–369.85 for summer scenario by app measurement (Figure 3.10a and 3.10b). Colorimeter measurements confirmed the trend. Varying temperatures in boxes stored at the same scenarios are caused by the temperature variations already existing in the boxes as described above. It can be concluded that the TTI is able to reflect temperature conditions inside the box when influenced by varying ambient temperatures, also at the coldest area near the reference product.

Concerning the TTI measurements at the customer level, six data sets could be evaluated. Measured TTIs were not in the same boxes as the received temperature data of the customers. The low response rates were presumably caused by the low availability of Android phones and errors during measurement attempts of the users inexperienced with the handling of the app. Successful app measurements were in a high range of SV_{RcGcBc} 289.31–383.31. High variations may be caused by the non-consistent measurement performances of the users, different light conditions during photographing and potentially older, low-resolution camera systems. In addition, the TTIs were probably not immediately measured after opening the box or were exposed to ambient temperatures. The uncertainties in the measurement conditions lead to the conclusion that the results of the customers can not be adequately evaluated.

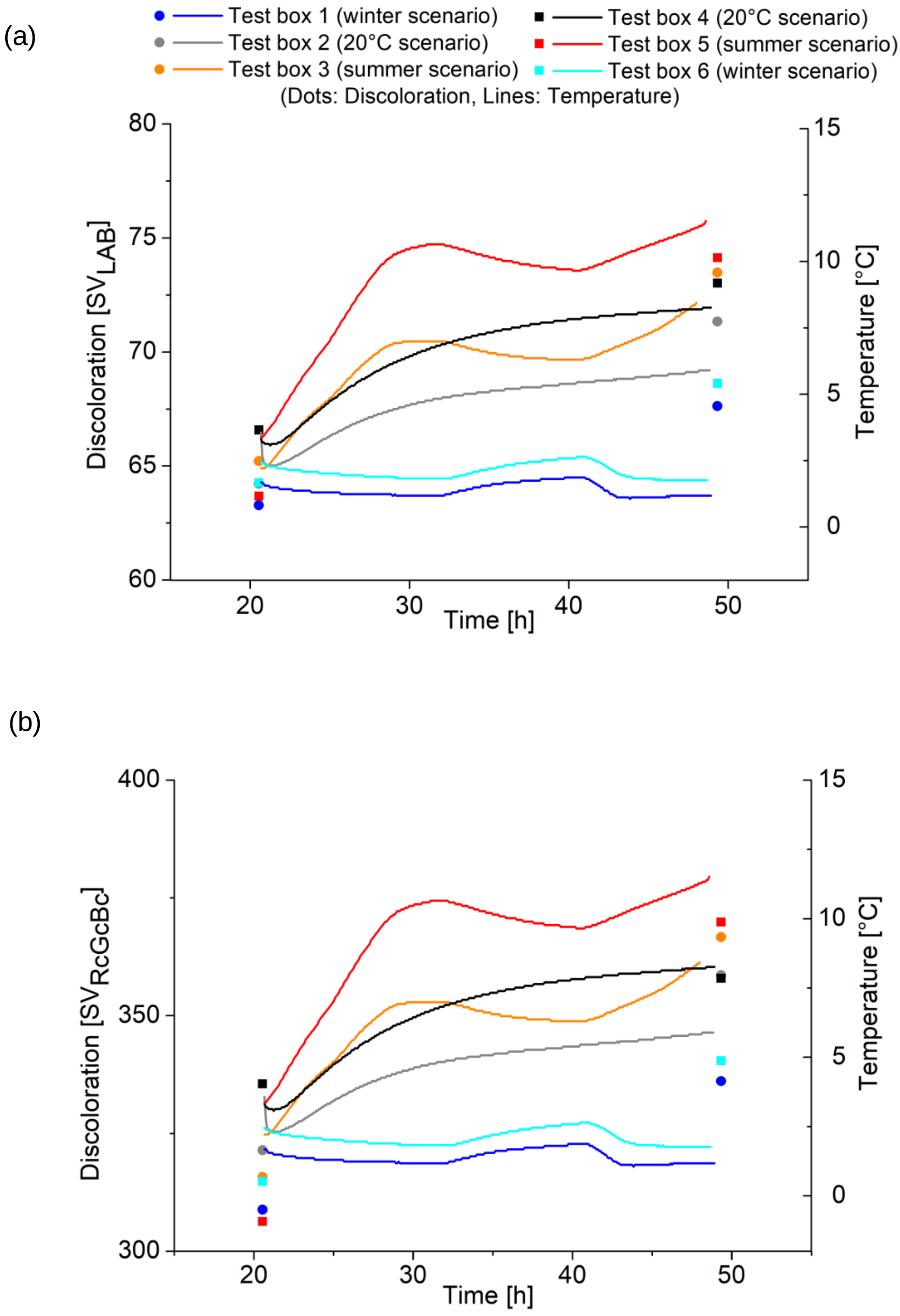


Figure 3.10. Discoloration of the TTI positioned on the flyer and temperature conditions inside the Test boxes during storage at different temperature scenarios (n=2 each), measured by (a) colorimeter and (b) app

Although the cold chain during transport of passively cooled boxes was well-maintained in this study, other studies in e-commerce revealed high variations of product temperatures in a range of 2.8°C to 25.4°C for perishable goods at the point of home delivery (Dautzenberg et al., 2017), and up to -11°C for a frozen meat delivery (Lehmann, 2017). Passively cooled boxes enable a more flexible delivery and a decrease in transport costs (Hofmann & Mathauer, 2018), however, it may happen that deliveries are not directly received by the customer (Nitsche & Figiel, 2016), enhancing the need for an adequate temperature monitoring. Our results showed that TTIs are able to reflect different temperature conditions also in boxes with mixed products and that the position close to the most sensitive product is useful to ensure that threshold temperatures are maintained. It is a promising tool for the temperature monitoring in e-commerce, offering a wide range of mixed perishable and non-perishable products (Fernie et al., 2010). Mixed boxes are also challenging in the B2B sector, thus, findings of this study can be transferred well. In the future, recommendations for temperature monitoring by TTI systems could be integrated in the guideline DIN 10543:2022–02 for regulating food e-commerce (Deutsches Institut für Normung e.V.). TTI systems can overcome concerns about e-commerce shopping of fresh produce due to the lack of information about visual freshness and product quality (Amcor, 2020; Grant et al., 2014; D. Zhang et al., 2016) and can furthermore fulfill the demand for enhanced sustainability (HDE, 2022). The study of Lorentzen et al. (2022) also showed that TTIs can be a beneficial tool for the consumer to evaluate the product quality after delivery. The QR code can be further used to integrate product information about origin of meat products and breeding circumstances, and thus to enhance consumers trust (Lehmann, 2017). The use of a smartphone app for the temperature check might meet with approval, as e-commerce customers show high affinity towards smartphones for online purchases (Morganti et al., 2014).

All pilot studies showed that TTIs are a valuable tool to reflect temperature conditions along different supply chains, which also turned out to be extremely necessary, as both survey and pilot studies had shown that typical weak points along the cold chain are still of high concern. TTIs combined with digital data sharing and exchange solutions thus can synchronize supply chain stakeholders and eliminate the uncertainty about temperature conditions (Marinelli et al., 2021; Verghese et al., 2015). In the B2C sector, TTI data could be furthermore linked to shelf life models for selected products which – especially with the increasing potential of artificial intelligences – can be a useful decision-making tool for companies and an incentive to expand digital processes. In the B2B supply chain, an efficient monitoring of typical weak points during transport and storage as well as the optimization of logistic processes is possible, especially for highly sensitive supply chains such as fish and seafood. The e-commerce sector represents a novel and challenging situation for a correct temperature monitoring, but an app-based TTI system offers a significant added value compared to a more expensive and complex deposit system, as customers can easily discard the label. The main challenge of a successful implementation in the different sectors, however, is the lacking willingness of stakeholders to implement an innovative temperature monitoring system, as the financial investment and the benefit for companies is not completely comprehensible yet. The inclusion of TTI systems in legal regulations as a strategy to reduce food waste, costs and to increase sustainable processes could advance the application in the future. The digitization of the TTI system can be supportive, as it can facilitate the application in practice.

3.4.3 Conclusion

In this study, the status quo of temperature monitoring and data exchange in perishable food supply chains was analyzed and the applicability of TTIs and an app-based readout system was tested to identify weak points and to optimize cold chain management. The survey has shown that mainly static product inspection is conducted and TTIs are still not widely used for temperature monitoring and that efficient data exchange amongst stakeholders is still challenging. However, the developments in digitization and the increasing willingness of stakeholders to exchange data offer promising possibilities for the introduction of TTI systems. TTIs measured by app were able to reflect temperature conditions in the three selected supply chains, revealing weak points and temperature abuses in the chain properly. The app-based system can contribute to an easier temperature monitoring and an efficient data exchange for the optimization of processes in the future and reduce the amount of food waste. Especially the application in e-commerce offers a valuable approach, as there is no temperature monitoring yet in passive cooled mixed boxes.

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4 Implementation of an app-based time-temperature-indicator system for the real-time shelf life prediction in a pork sausage supply chain

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4.1 Abstract

Time-temperature-indicators (TTI) combined with predictive modeling are helpful tools for avoiding the increasing amount of food waste and the associated waste of resources along the food supply chain. Successful implementation of these systems in practice is still absent due to missing digital technologies for real-time shelf life prediction. This study aimed to validate a novel app system developed for the digital read-out of OnVu™ TTIs and the shelf life prediction of perishable products along the raw pork sausage supply chain. Therefore, a kinetic shelf life model of raw pork sausage was developed based on microbial parameters. A dynamic TTI model was developed based on app-measured TTI data and validated on a laboratory scale to prepare for the pilot study. In the pilot study, the shelf life prediction of TTIs based on app measurements was validated under practical conditions. Results showed that the spoilage kinetics of raw pork sausage could, in general, be reflected by the OnVu™ TTI kinetics based on the app's color measurements. The pilot study showed that predicted and measured TTI color values by the app were in good agreement with accuracy factors of 1.02–1.03; however, slight differences in shelf lives revealed that the prediction model must be further improved by integrating more data. Although variances in the hourly range could be seen between the predicted shelf life based on TTI app measurements and the real shelf life of raw pork sausage, the study serves as a proof of concept for the general useability of the app for shelf life prediction because it showed that TTI and product kinetics were highly comparable. Further technical adjustments to the app and the adaptation of the charging time may further improve the shelf life prediction by the app along the raw pork sausage supply chain.

4.2 Introduction

Around 340 megatons meat are produced globally annually; the number is expected to increase further in the next years (FAO, 2022; OECD & FAO, 2022). The meat supply chain is characterized by complex production processes and supply networks and an intense consumption of energy and environmental resources, due to excessive land use for livestock farming and feed cultivation. Meat production is responsible for more than 50 % of the total emissions of greenhouse gases (GHG) in the agricultural sector (Benning, 2021; Godfray et al., 2018; Leip et al., 2015; Umweltbundesamt, 2018; Weiss & Leip, 2012) and contributes to nearly one-third of the global agricultural water food print.

Food waste in meat supply chains is a very critical issue, especially due to the high environmental impact. Several studies show that more than 20 % of the produced meat is wasted (Caldeira et al., 2019; Gustavsson, 2011; Karwowska et al., 2021). The causes are multifactorial, including insufficient cooling, temperature interruptions, and inadequate transport and storage conditions, resulting in spoilage and, thus, in presenting a hazard to product quality and safety (Bilska et al., 2020; Canali et al., 2017; Flanagan et al., 2019; Lipinski, 2020; Nychas et al., 2008; Parfitt et al., 2010). Furthermore, inadequate control and information exchange along the chain can lead to food waste (Canali et al., 2017; Muriana, 2017). However, meat is also discarded at the retailer and consumer level when the product's shelf life is expired (Karwowska et al., 2021; Lebersorger & Schneider, 2014; Neff et al., 2019), even though the product is often still of good quality when stored at adequate temperatures. Continuous temperature monitoring is required to control the cold chain and the spoilage processes to prevent the discard of products.

The emerging amounts of food waste in the meat supply chain and the accompanying political efforts to increase the reduction of food waste and, thus, sustainability have brought intelligent packaging and predictive modeling solutions back into focus. Time-temperature-indicators (TTI) are labels, that change their color in dependence on temperature based on various function principles, e.g. (electro)chemical, mechanical, enzymatic, or microbial (Kerry et al., 2006; Smolander et al., 2004; Taoukis & Labuza, 2003). They can monitor temperature continuously from production to the end consumer and work as a helpful tool for all stakeholders to detect weak points (Kreyenschmidt, Christiansen, et al., 2010; Taoukis & Labuza, 1989). The indicators, combined with predictive shelf life models for specific products, work not only as a temperature control but also as a freshness indicator. The mathematical models, describing growth kinetics and temperature dependency, are based on the spoilage kinetics of the products. Combined with the temperature history and additional chain-specific information, they can be implemented in cold chain management (Bruckner et al., 2013; Koutsoumanis et al., 2006; Kreyenschmidt, Hübner, et al., 2010; Raab et al., 2008). The combination with predictive models is necessary to estimate specific product shelf lives based on real-time temperature data of the supply chain with the help of software systems (Corradini, 2018; Labuza & Fu, 1993; Nychas et al., 2008). Based on that, a dynamic shelf life can be implemented (Albrecht et al., 2021; Yimenu et al., 2019). In case of temperature interruptions, goods can be redistributed or sold before they are spoiled. TTIs can also indicate ideal cold chain conditions and the associated, possibly longer, product shelf life. This capacity can lead to a higher efficiency of the entire supply chain, including used resources. Their potential is already proven, implying that by using TTIs, food waste can be reduced by 35 % (Heising et al., 2017; Rossaint & Kreyenschmidt, 2015), consequently decreasing GHG emissions and the negative environmental impacts of livestock farming (Clark et al., 2020; Gustavsson, 2011; Leip et al., 2015). However, even if many predictive models exist, and intelligent packaging solutions are becoming more technologically advanced, a comprehensive implementation in the meat supply chain is still absent. In the past, one of the main reasons for the missing implementation was a lack of standardized, digital read-out systems, such as smartphone apps, which can be used by all actors along the supply chain. This type of system is already technically possible, as the study by Waldhans et al. (2023) revealed by developing an app-based read-out system for TTIs. In the study by Waldhans et al. (2024), TTI temperature monitoring by an app was tested in different perishable supply chains, and the results revealed monitoring of temperature and identification of temperature interruption during transports by the app. However, the validation of the shelf life prediction system in practice is still missing.

Thus, this study aimed to validate a novel, app-based read-out system for the OnVu™ TTI system, which runs on a standard smartphone to monitor the shelf life of perishable raw pork sausage along the cold chain. The OnVu™ TTI is a well-investigated, polymer-based label that is highly adjustable to different products and shelf life. In the first part of the study, a shelf life model of raw pork sausage was developed by conducting storage tests at different constant and dynamic temperatures under laboratory conditions. Based on previously app-measured TTI data, a dynamic TTI shelf life model was developed and validated on a laboratory scale. Then, the applicability of the app as a TTI read-out and shelf life prediction system for raw pork sausage was tested in a pilot study of raw pork sausage under real processing, transport and storage conditions. The newly developed app, described by Waldhans et al. (2023), was used and validated in the pilot study for the TTI color read-out and the digital calculation of shelf lives.

4.3 Materials and methods

4.3.1 Experimental design

The study comprised two experimental parts. In the first part, the microbial and sensory spoilage of raw pork sausages packed under a modified atmosphere (MA) was investigated, and a shelf life model was developed. The model was used to describe the spoilage kinetics of the sausages and to assess whether they could be described with the discoloration kinetics of the OnVu™ TTI. Therefore, storage trials under five isothermal temperature conditions were conducted to investigate microbial and sensory spoilage as well as other quality parameters. Furthermore, two non-isothermal scenarios on a laboratory scale were conducted to validate the TTI shelf life model. In preparation for the second part of the study, a dynamic TTI model was developed based on previous TTI data and validated on a laboratory scale. In this part, a pilot study in a German supply chain for raw pork sausage was conducted to test the shelf life prediction of the sausages using a novel app-based read-out system for TTIs along the supply chain. The well investigated OnVu™ TTI was used in this study. Here, raw pork sausage samples were tagged with TTIs adjusted to the product's shelf life immediately after the sausages were produced. Packed samples were transported over a real, temperature-controlled supply chain with a transshipment point at the factory sale. Afterward, samples were stored at the laboratory under four different constant temperature scenarios to simulate different storage conditions in households and to test the accuracy of shelf life prediction by the app.

4.3.2 Development of a kinetic shelf life model for raw pork sausage

4.3.2.1 Sample description and study design

The investigated product was raw pork sausage processed and provided by a German company; the product consists of finely chopped sausage meat (87 % pork, water, table salt, spices, caraway, dextrose, sugar, glucose syrup, sodium acetate, sodium citrate, and diphosphate) wrapped in pork skin. Each sample package (750 g) consisted of five sausages (150 g each), packed under an MA (70 % O_2/30 % CO_2). For the first part of the study, which was the development of the shelf life model based on investigating spoilage kinetics under laboratory conditions, the sausages were transported to the laboratory after production in a cooled transport by an external provider. For all tests at the laboratory, the samples were stored in low-temperature, high-precision incubators (MIR 153, SANYO Electric Co., Ora-Gun, Gumma, Japan). The temperature was controlled every 10 min by data loggers (Testo SE & Co. KGaA, Titisee-Neustadt, Germany) during transport and storage.

In the first part of the study, seven storage trials were conducted. Five storage trials were conducted under different isothermal conditions (2°C, 4°C, 7°C, 10°C, 15 °C) to investigate the spoilage kinetics and quality loss of raw pork sausage and to identify the specific spoilage organism (SSO) for shelf life predictions. The selected isothermal temperatures are classical storage temperatures applied in shelf life studies (Albrecht et al., 2021; Bruckner et al., 2013), representing a suitable range of storage conditions. Two trials were conducted under different non-isothermal temperature conditions to validate the shelf life predictions. Temperature fluctuations were set at the beginning of microbial growth (3 shifts to 15 °C for 4 h at 26, 48 and 72 h after production) in the first trial. These shifts should simulate the temperature fluctuations during transport and transshipment points at the beginning of the supply chain. In the second trial, shifts during the exponential growth phase of bacteria (3 shifts to 15°C for 4 h at 168, 194 and 214 h after production) were set to simulate the potential temperature fluctuations during the storage phase at the retailer and consumer; 15°C was selected as a standardized temperature to simulate a violation of the cold chain. As a reference, the constant 4°C trial was conducted in parallel to the non-isothermal scenarios. Microbial, sensory, and quality parameters were investigated 24 h after production (arrival at the laboratory after transport) and at defined investigation points during storage.

4.3.2.2 Microbial Analysis

Microbial analyses of samples were conducted at defined investigation points by applying classical microbial techniques. A mixed sample of sausages in each packaging, consisting of meat emulsion and skin, was obtained with a round stamp (∅2.5 cm) at two points on three sausages, and weighed at 25 g in a filtered and sterile stomacher bag and filled up by adding 225 g of saline tryptone diluent (0.85 % NaCl, Oxoid GmbH, Basingstoke, United Kingdom; 0.1 % tryptone, VWR International GmbH, Darmstadt, Germany). The sample was then homogenized for 60 s in a Stomacher 400 (Kleinfeld Labortechnik, Gehrden, Germany). A tenfold dilution series was made using the same saline tryptone diluent. Appropriate dilutions were dispensed on different growth media to prepare two replicates for each dilution. The growth of total viable count (TVC) and lactic acid bacteria (LAB) were determined by the pour plate technique, dispensing 1 ml of sample dilution each on plate count agar (PC) (Merck KGaA, Darmstadt, Germany) and De Man, Rogosa and Sharpe Agar (MRS) (Merck KGaA, Darmstadt, Germany), respectively. PC agar plates were incubated at 30°C for 72 h, and MRS agar plates at 37°C for 72 h. *Brochothrix thermosphacta* were identified by the drop-plate technique using the streptomycin inosit toluylene red agar (Sheep Blood Agar Base, Oxoid Limited, Hampshire, England) with supplements (Merck KGaA, Darmstadt, Germany; Carl Roth

GmbH & Co. KG, Karlsruhe, Germany) during an incubation period of 48 h at 25°C. The growth of *Pseudomonas* spp. was investigated by the spread-plate technique using the Pseudomonas CFC agar base (Merck KGaA, Darmstadt, Germany) supplemented with the Glycerol and CFC selective supplement (Merck KGaA, Darmstadt, Germany). Enterobacteriaceae were detected on violet red bile dextrose agar (Merck KGaA, Darmstadt, Germany) by applying an overlay treatment and incubating the plates for 24 h at 37°C. Yeasts and molds were determined with the spread-plate technique on Yeast Extract Glucose Chloramphenicol agar (Merck KGgA, Darmstadt, Germany). The plates were incubated for 120 h at 25°C. In the pilot study, the samples were examined only for the growth of TVC and LAB, as LAB was identified as the SSO of the product. Microbial counts were determined and calculated in $\log_{10}$ CFU/g. The spoilage level reached 7.0 $\log_{10}$ CFU/g for TVC, according to the specifications of the production plant, and 6.5 $\log_{10}$ CFU/g for LAB including a safety margin.

4.3.2.3 Sensory and quality parameter analysis

In parallel to the microbial analysis, a sensory evaluation of the samples was conducted to evaluate potential differences between microbial analysis and sensory perception. A trained sensory panel of three to four participants evaluated color, odor and texture of the raw pork sausages. A 5-point scale was used for evaluation, with five for the highest sensory quality and one for the lowest. Based on the evaluation of the attributes, a sensory index (SI) was calculated using the following equation.

$$SI = \frac{2 * C_o + C_i + 2 * O + T}{6} \tag{4.1}$$

where SI: sensory index at time [h]; C_o/ C_i: evaluation of color outside and inside; O: evaluation of odor; T: evaluation of texture. The sensory shelf life limit was reached at SI = 2.8.

Furthermore, the quality parameters (gas atmosphere, pH value, and color value) were investigated at the defined investigation points with appropriate measuring instruments, and a texture profile analysis was made. The parameters were not included in the development of the shelf life model because they showed a less reliable dependence on time and temperature. Therefore, they were not discussed in this chapter.

4.3.2.4 Data analysis and modeling

The microbial and sensory data were fitted using the statistical software OriginPro 8.0G (OriginLab Corp., Northampton, MA, USA). Microbial data were modeled by combining models on a primary and secondary level, according to Bruckner et al. (2013). On a primary level, microbial growth as a function of time was described using the modified Gompertz model (Gibson et al., 1987):

$$N_t = N_0 + a * e^{-e^{-k*(t-xc)}} \tag{4.2}$$

where N_t: microbial count [$\log_{10}$ CFU/g] per time t [h]; N_0: lower asymptotic line of the growth curve/the initial bacterial count [$\log_{10}$ CFU/g]; a: amplitude (difference between the upper asymptotic line of the growth curve/the maximum bacterial count N_{max} [$\log_{10}$ CFU/g] and N_0); k: relative growth rate at the time [h^{-1}]; xc: reversal point (time at which maximum growth rate is obtained) [h]; t: time [h].

With a secondary model, the temperature dependency of microbial growth was assessed using the Arrhenius approach to plot the calculated relative growth rates (k) as a function of temperature:

$$\ln(k) = \ln(k_0) - \frac{E_a}{R} \cdot \frac{1}{T} \tag{4.3}$$

where k: reaction rate [h^{-1}]; k_0: constant [h^{-1}]; E_a: activation energy [kJ mol^{-1}], R: ideal gas constant [8.314 J mol^{-1} K^{-1}]; T: absolute temperature [K].

For the shelf life prediction under non-isothermal conditions, primary and secondary models were combined according to Bruckner et al. (2013) and Kreyenschmidt, Hübner, et al. (2010). Assuming that the initial count (N_0) and the maximum bacterial count (N_{max}) were constant, values were estimated by averaging the N_0 and N_{max} of the LAB growth at the constant temperatures, as calculated using the Gompertz model on the primary level. The calculation yielded an N_0 of 2.81 $\log_{10}$ CFU/g and an N_{max} of 7.90 $\log_{10}$ CFU/g.

The parameter a was then calculated with the following equation:

$$a = N_{max} - N_{min} \tag{4.4}$$

In non-isothermal scenarios with fluctuating temperatures, the reversal point xc has to be individually calculated for every interval with a new temperature and the current bacterial count. For the first interval, xc was calculated based on the exponential regression of xc against temperature under isothermal conditions. Exponential regression was used, as it most accurately describes the relationship between xc and temperature.

$$xc = a * e^{-\frac{T}{t}} + y_0 \tag{4.5}$$

where *xc*: reversal point [h]; *a*: amplitude [h^{-1}]; *T*: temperature in the interval [K]; *t*: time constant [h]; y_0: offset [h]

The relative growth rate k of the interval was calculated using the secondary model (equation 4.6) and by inserting the respective temperature. Using the calculated *xc* and *k*, the bacterial count at the end of the first temperature interval could be calculated. Further calculations of the bacterial counts and the reversal points of each interval were conducted with equations 4.6 and 4.7:

$$N(t_e) = a * e^{-e^{-k_T*(t-xc)}} + N_0 \tag{4.6}$$

where $N(t_e)$: bacterial count at the end of the interval [$\log_{10}$ CFU/g] with $e = 1,\ldots n$: number of intervals; *a*: amplitude (difference between the upper asymptotic line of the growth curve/the maximum bacterial count N_{max} [$\log_{10}$ CFU/g] and N_0 [$\log_{10}$ CFU/g]); k_t: relative growth rate estimated by secondary modeling [h^{-1}]; *t*: time [h]; *xc*: reversal point calculated for the interval [h]; N_0: initial bacterial count [$\log_{10}$ CFU/g].

$$xc = \frac{\ln\left(-\ln\left(\frac{N(t_{e-1}) - N_0}{a}\right)\right)}{k_T} + t \tag{4.7}$$

4.3.3 Characterization of the OnVu™ TTI, app-based color measurement and shelf life prediction app

To investigate the use of a novel app for the shelf life prediction by TTIs, the well-investigated OnVu™ TTI (Batch 21.06.2021, Color Batch 00552HN8, Ciba Specialty Chemicals & Freshpoint, Basel, Switzerland, patent WO/2006/048412) was used for all investigations. It contains a pigmented water ink, which turns blue after activation by UV light and turns white after a time- and temperature-dependent discoloration process. The charging times with UV light at activation define the initial color value of the label and the length of the discoloration process and can, therefore, be adapted to different shelf lives. For the activation of the labels with different charging times, a UV light charger (GLP 80/56 TTI, Bizerba, Germany) was used to automatically attach a protective UV filter

(LOT#146 000018272) on the label by thermal transfer print after the activation process. The newly developed app was used to measure the TTI discoloration immediately after charging and at defined investigation points during storage trials, according to Waldhans et al. (2023) with a Nokia 7.2 Dual-SIM Android™ 9.0 48m pixels smartphone (Nokia Oyj, Espoo, Finland). Measurements were performed at established measuring stations with a daylight lamp (1620Lm, 6500K, Tageslichtlampen24.de, Kiel, Germany) for sufficient illumination of the pictures, adjusting to a 2x zoom. Reference color measurements were conducted in parallel with EyeOne i1 Basic Pro1 colorimeter (X-rite; Gretag Macbeth, Regensdorf, Switzerland) at all investigation points.

4.3.4 Development of a dynamic TTI model and validation on a laboratory scale

A dynamic TTI model for app measurements was developed based on the data, and the TTI discoloration model was developed by Waldhans et al. (2023) to enable TTI shelf life prediction at fluctuating temperatures. The amplitudes of the discoloration curves at constant temperature conditions were first optimized to enable a calculation of the discoloration end point by the model, even for high charging times and low temperatures. The dynamic model was developed according to Albrecht et al. (2020) by combining logistic models for the description of the discoloration and Arrhenius fits for the description of the temperature. The temperature dependency of the amplitude *a* was described by linear regression based on the results for *a* at different charging times and temperatures. The validation of the dynamic TTI model was conducted under laboratory conditions with TTI storage tests at a dynamic temperature scenario. Therefore, OnVu™ TTI labels were charged at different charging times of 800, 1200, 1500, and 1800 milliseconds (ms), eight labels each, and stored at a determined dynamic temperature scenario with 41 h at 2°C, 48 h at 7°C, and 168 h at 10°C to simulate temperature fluctuations in practice. TTI discoloration was measured at defined interval points during the storage time with the app and colorimeter, as previously described.

4.3.5 Validation of the app-based system for the shelf life prediction of raw pork sausage by the OnVu™ TTI under practical supply chain conditions

The focus of the second part of the study was to validate the app-based read-out system for TTIs under practical conditions. Therefore, a pilot study was conducted in a German supply chain for raw pork sausages. Figure 4.1 shows an overview of the pilot study, including its steps and storage conditions. Here, 384 samples of raw pork sausage were packed and immediately equipped with OnVu™ TTI labels at the processing company. Labels were activated with a charging time of 1500 ms under chilled temperature conditions at the company's production hall, according to Albrecht et al. (2020). Activated labels were attached to single-unit packaging samples on two layers of self-adhesive white paper to ensure a consistent background for color measurements. The samples were placed on two pallets, that were placed at different locations in an actively cooled transporter. Then, the samples were distributed from the production plant to the factory sale as a transshipment point on a regular transport route. Finally, the samples were transported to a laboratory at the University of Bonn for subsequent storage at four different constant temperatures (2°C, 4°C, 7°C, and 10°C) to simulate storage conditions at the consumer.

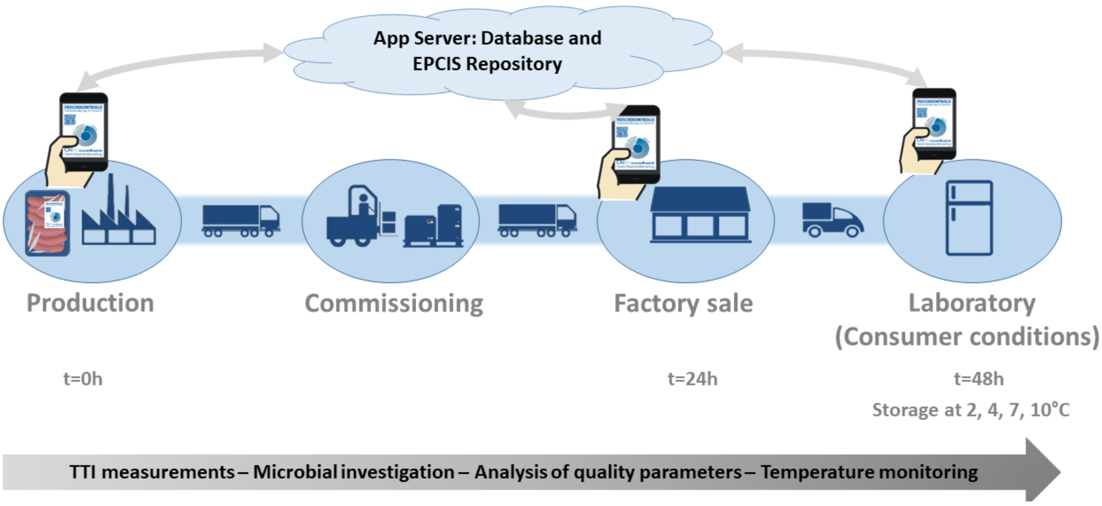

Figure 4.1. Scheme of the pilot study in a German supply chain for raw pork sausages with specific measurement points

App measurements of the TTI discoloration and prediction of the shelf life were conducted at individual investigation points for the different temperatures. The color measurements at the initial point and the factory sale were performed free-handed, and measurements at the laboratory were conducted in a darkroom using a fixed smartphone holder with the light and distance settings described previously. Reference measurements were conducted in parallel with the colorimeter.

In addition to the TTI measurements, spoilage of raw pork sausage was assessed at similar investigation points by microbiological investigation to compare the shelf life prediction of the TTI with the actual microbial shelf life. Eight samples of raw pork sausage were taken at each investigation point. The growth of LAB as the detected SSO of the product, as well as the growth of TVC, were investigated, as described in section 4.3.2.2. A sensory evaluation of the samples was conducted in parallel, as described in section 4.3.2.3. Data analysis and modeling were conducted similarly to the one described above.

4.3.6 Data analysis and modeling

4.3.6.1 Modeling the shelf life of TTIs

TTI discoloration was modeled using the kinetic approach described by Taoukis & Labuza (1989) and Tsironi et al. (2008). On the primary model level, square values (SV) of the detected RGB color values of the blue dot corrected by white balance with the surrounding white points, according to Waldhans et al. (2023), were calculated with equation 4.8.

$$SV_{R_cG_cB_c} = \sqrt{{R_c}^2 + {G_c}^2 + {B_c}^2} \tag{4.8}$$

where SV: square value; R_c; G_c; B_c: corrected color values by white balance. The SV of the LAB color data detected by colorimeter was likewise calculated with equation 4.9.

$$SV_{LAB} = \sqrt{L^2 + a^2 + b^2} \tag{4.9}$$

where L: lightness/luminance; a: red and green components of the color; b: yellow and blue components of the color.

The discoloration of both SV_{RcGcBc} and SV_{LAB} was then described by the logistic model according to Kreyenschmidt, Christiansen, et al. (2010) and Albrecht et al. (2020).

$$SV_{LAB;\,R_cG_cB_c} = \frac{a}{1 + e^{-k(t-xc)}} \tag{4.10}$$

where a: amplitude; k: reaction rate (h^{-1}); xc: reversal point (h); t: time (h) for each logistic model in CIELAB and RGB color systems.

The remaining TTI shelf life at selected time points was calculated using equation 4.11. Therefore, measured color values at the selected time points were used to calculate the reversal point for every time interval, according to Albrecht et al. (2020).

$$t_{rem} = -\frac{\ln(\frac{a}{SV_{End}} - 1)}{k + xc} - t_{exp} \tag{4.11}$$

where a, k and xc are based on the parameters of the shelf life prediction model and the measured TTI color value for the respective time interval in combination with the expected storage temperature, SV_{End}: 344 for TTI shelf life calculation in RGB color system according to Waldhans et al. (2023), 71 in CIELAB color system according to Kreyenschmidt, Christiansen, et al. (2010); t_{exp}: expired time since TTI charging (h).

The total TTI shelf life was calculated by plugging in the respective fitting results of the models and the respective discoloration end points as follows:

$$t_{SL} = -\frac{\ln(\frac{a}{SV_{End}} - 1)}{k} + xc \tag{4.12}$$

with a, k and xc based on the parameters of the shelf life prediction model for the time interval in which the discoloration end point is reached.

4.3.6.2 Calculating the quality of shelf life models

The performances of the product and TTI shelf life models were validated by determining the bias and accuracy factor described by Ross (1996). Therefore, predicted and observed microbial counts and predicted and observed TTI color values, respectively, were compared using the following equation:

$$B_f = 10^{(\sum \log\left(\frac{predicted_i}{observed_i}\right)/n)} \tag{4.13}$$

where B_f: bias factor; $predicted_i$: predicted bacterial growth values/TTI color values; $observed_i$: observed bacterial growth values/TTI color values; n: number of observations.

To additionally calculate the accuracy of the model and to prevent the effect of concurrent underestimation and overestimation resulting in a not meaningful bias factor, the accuracy factor is considered the second parameter for the evaluation of the models:

$$A_f = 10^{(\sum \left|\log\left(\frac{predicted_i}{observed_i}\right)\right|/n)} \tag{4.14}$$

where A_f: accuracy factor; $predicted_i$: predicted bacterial growth values/TTI color values; $observed_i$: observed bacterial growth values/TTI color values; n: number of observations.

Regarding the comparison between predicted and observed values, a bias factor of 1.00 reflects an exact agreement between predicted and observed values. A bias factor of >1.00 indicates that the model overestimates bacterial growth or TTI color, respectively; therefore, the model is a "fail-safe" model. Consequently, a bias factor of <1.00 means the model underestimates the growth: thus, the model it is categorized as "fail-dangerous". Likewise, the accuracy factor of 1.00 reflects an exact agreement of predicted and observed values, whereas a higher accuracy factor suggests a less accurate prediction of the values.

4.4 Results and discussion

4.4.1 Development of a kinetic shelf life model for raw pork sausage

The growth of TVC and LAB on raw pork sausage at different constant temperatures could be described very well by the modified Gompertz model (a R^2 value 0.994 to 0.998 for TVC and 0.995 to 0.999 for LAB). Bacterial counts for TVC detected at 24 h were in a range of 3.53 ± 0.11 to 4.67 ± 0.11 $\log_{10}$ CFU/g, resulting in 7.89 ± 0.06 to 8.59 ± 0.15 $\log_{10}$ CFU/g at the end of storage. The bacterial counts of LAB were between 2.48 ± 0.17 and 3.17 ± 0.04 $\log_{10}$ CFU/g at 24 h and 7.32 ± 0.14 and 8.50 ± 0.13 $\log_{10}$ CFU/g at the end of the respective storage trials. Low standard deviations (SD) of the samples at all investigation points (0.02–0.41) further support the reliability of the shelf life model. The growth curves of LAB are shown in Figure 4.2a. As the growth of LAB was comparable to the growth of TVC at all temperatures, LAB could be identified as the SSO of MA-packed raw pork sausage in this study. The differences in the initial counts of TVC and LAB are caused by the fact that the initial microflora is characterized by multiple species, whereas the SSO grows faster during storage and thus dominates other bacteria (Koutsoumanis & Taoukis, 2005). LAB is already known as one of the bacterial groups dominating the spoilage of MA-packed products (Koutsoumanis & Taoukis, 2005; O'Sullivan, 2016) and is revealed as the SSO on MA-packed raw pork sausage, indicating initial and end bacterial counts in a range of 3.5 to 8.5 $\log_{10}$ CFU/g (Bouju-Albert et al., 2018; Cocolin et al., 2004; Raimondi et al., 2018), as well as on MA-packed poultry sausages (Lerasle et al., 2014).

Other investigated spoilage organisms did not demonstrate a significant growth or any growth at all, reaching maximum bacterial counts of 2.0 $\log_{10}$ CFU/g for Enterobacteriaceae to 4.9 $\log_{10}$ CFU/g for *Brochothrix thermosphacta*; thus, they were not considered further for this study. The temperature dependency of the spoilage processes could be described well by the Arrhenius equation (R^2 = 0.959) (Figure 4.2b). The E_a for MA-packed raw pork sausage was calculated to be 23.45 kcal/mol, which was in good accordance with E_as of other MA-packed products, such as 21.99 kcal/mol for fresh pork loins (Albrecht et al., 2021) and 23.97 kcal/mol for fresh fish (Tsironi et al., 2011). Furthermore, the calculated E_a shows a difference of less than 5 kcal/mol compared to the E_a of the OnVu™ TTI at 24.25 to 27.41 kcal/mol, respectively (Waldhans et al., 2023); thus, the shelf life kinetics of the product can be reflected by the TTI kinetics (Taoukis et al., 1999).

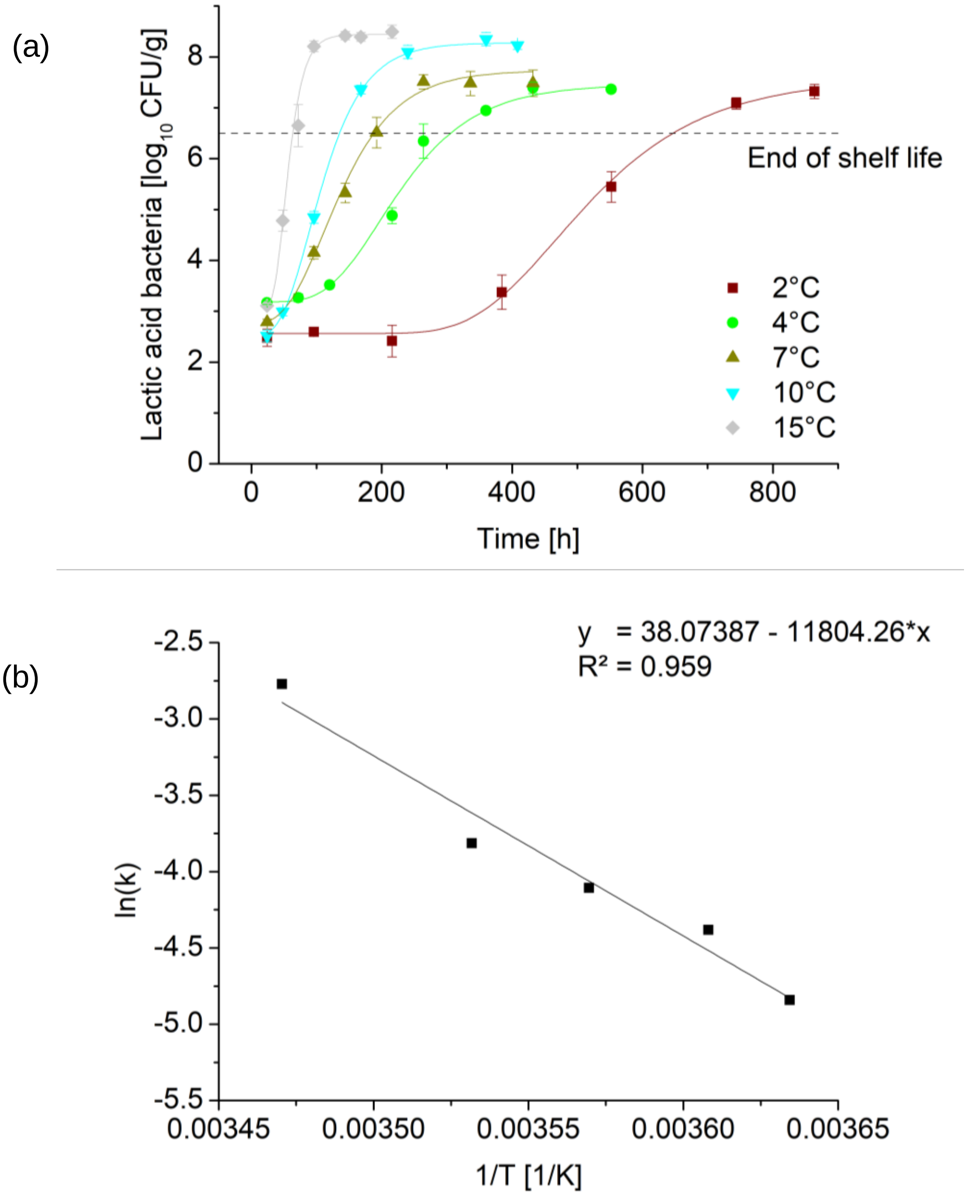

Figure 4.2. (a) Growth of Lactic acid bacteria on raw pork sausage at different constant temperatures modeled by modified Gompertz model. (b) Temperature dependency of the relative growth rate k modeled by Arrhenius equation (n = 5 per measuring point)

Concerning different batches, the bacterial counts for LAB at the first investigation point at 24 h differed by less than one log level, which is optimal both for the accuracy of the shelf life model, and a reliable reflection by TTIs. The microbial shelf lives for LAB and the sensory shelf lives at constant storage temperatures are shown in Table 4.1. Microbial growth is significantly slowed at 2°C, indicating that other changes, such as oxidative processes, occurred during storage (Robertson, 2010). However, the microbial shelf lives were shorter than sensory shelf lives at 11 to 87 h, respectively, indicating the importance of a monitoring tool, such as TTIs, as consumers could misinterpret the sensory evaluation, especially at higher temperatures.

Table 4.1. Microbial (LAB) and sensory shelf lives of raw pork sausage stored at different constant temperatures

Temperature [°C]	Microbial shelf life [h] 	Sensory shelf life [h]
2	647	683
4	306	317
7	188	233
10	135	222
15	63	93

Figures 4.3a and 4.3b show the observed growth of LAB in the dynamic scenarios compared to the predicted values by the developed shelf life model. Predicted and observed growth data were in good agreement in both scenarios with R^2 of 0.966 (S1) and 0.977 (S2). The performance evaluation of the model according to Ross (1996) revealed bias factors of 0.95 for S1 and 0.96 for S2. Consequently, the model could be classified as "fail-dangerous" in both scenarios, as it generally underestimated the growth of LAB. However, the underestimation of the growth could mainly be seen at the lag phase, whereas growth prediction at the end of a shelf life and higher bacterial counts are more approximated to observed values so that the prediction is reliable at this critical point. Comparable results could be seen for the shelf life model developed by Bruckner et al. (2013) for aerobe-packed pork and poultry. The accuracy factor in this study was calculated to be 1.07 for S1 and 1.06 for S2. Thus, the model predictions showed a

variance of 7 % and 6 %, respectively, for S1 and S2 from the observed data, indicating a high accuracy of the model. The observed shelf life was calculated to be 299 h for S1 and 262 h for S2. The predicted shelf life for both scenarios was 285 h, as the effective temperature was equal. Therefore, the scenarios provided information on the growth behavior of LAB when temperature interruptions occurred in different phases of the supply chain.

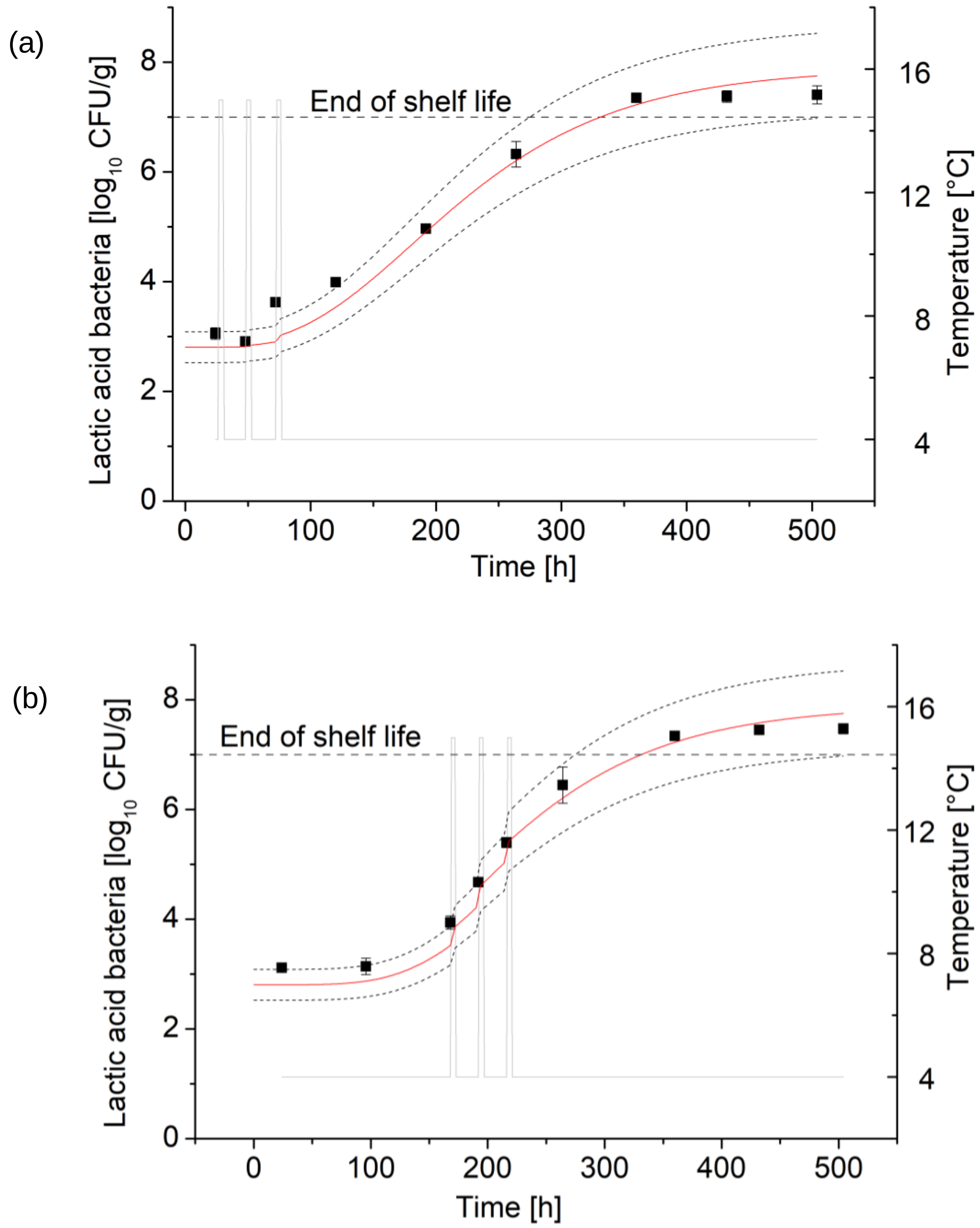

Figure 4.3. Observed and predicted growth of Lactic acid bacteria on raw pork sausage under dynamic temperature conditions. (a) Scenario 1 with temperature interruptions in the lag phase. (b) Scenario 2 with temperature interruptions in the exponential phase (n=5 per measuring point)
(■) observed growth, (—) predicted growth, (- - -) ±10%, (—) temperature profile

4.4.2 Development of a dynamic TTI model and validation on a laboratory scale

The comparison of app-measured and predicted TTI values calculated by the developed dynamic TTI model showed, in general, a good agreement, yielding results of R^2 between 0.931 and 0.968 for scenarios with different TTI charging times. Bias factors for the different trials ranged between 1.00 and 1.02, and accuracy factors ranged between 1.02 and 1.03. Observed shelf lives were calculated to be between 98 and 140 h, whereas predicted shelf lives ranged from 69 to 109 h, depending on the TTI charging times. Especially at the beginning and end of the discoloration, the predicted and observed values were in very good agreement; however, the model slightly overestimated the discoloration at the point of shelf life end. The result suggest that the model can be classified as “fail-safe”, which offers a certain safety margin for the TTI shelf life prediction.

4.4.3 Validation of the app-based system for the shelf life prediction of raw pork sausage by the OnVu™ TTI under practical supply chain conditions

The initial TTI color values at the charging point (n = 262) were SV_{RcGcBc} at 209.66 ± 12.36 measured by the app, which showed that, in general, a reproducible charging under practical conditions was possible, which was also shown by Albrecht et al. (2020) and Kreyenschmidt, Christiansen, et al. (2010). Reference measurements by colorimeter were likewise stable with SV_{LAB} at 55.57 ± 0.22. The reproducibility of the charging process is a prerequisite for the successful application of the TTI and its measurement in practice. The slight differences revealed by standard deviations might be due to small fluctuations in environmental temperature conditions during the charging process, which led to a certain variation in the initial color value of the TTI. The mean temperature on the pallet during transport along the supply chain was 3.4°C ± 1.29, suggesting a well-maintained cold chain with only negligible deviations. The mean remaining shelf lives at different investigation points during the pilot study based on real-time app measurements for the different temperature trials are shown in Table 4.2. The calculated total shelf lives for 4°C, 7°C and 10°C based on app measurements are likewise displayed in Table 4.2. For storage at 2°C, the remaining shelf lives at investigation points and the total shelf life could not be calculated by app measurements and the shelf life model. Low storage temperatures and high initial charging values are known challenges in the accurate prediction of the OnVu™ TTI; thus, in these cases, the shelf life model must be optimized.

The predicted remaining shelf lives are based on the TTI shelf life model. TTI color values measured by the app at different investigation points were then integrated to adjust the prediction based on real-time measurements (Figure 4.4a and 4.5a). Predicted and measured TTI color values were in high accordance during the pilot study, including transport and storage at different temperatures, showing high goodness of fit values with B_f = 1.00–1.01, A_f = 1.02–1.03 and R^2 = 0.93–0.99. Colors of the TTI predicted by the shelf life model or based on actual app measurements resulted in differences in shelf lives ranging between 14 and 27 h (Table 4.3), revealing reasonable differences and indicating that it can generally reflect the actual TTI color values at different measurement points. By capturing more app measurements along the chain, the model accuracy and the reliability of the shelf life prediction can be further improved. Combining TTI app measurements with the shelf life prediction model can be valuable for calculating real-time shelf lives along the chain based on varying temperature conditions.

In parallel to the app measurements of the TTI shelf life, microbial growth of LAB was investigated. The initial bacterial count of LAB at the point of production and packaging (t = 0) was 3.42 ± 0.13 $\log_{10}$ CFU/g and is slightly higher than the bacterial counts detected in the laboratory shelf life studies. The minor difference could be explained by natural variations, a higher bacterial load of the raw ingredients and high ambient temperatures during processing and storage. However, the comparison of the initial bacterial counts in both parts of the study was limited, as bacterial counts in the first part of the study were conducted at 24 h. Compared to later time points of the lag phase, bacterial counts could be higher at 0 h due to the adaptation time of the microorganisms at specific storage temperatures. This observation was also made by Bruckner et al. (2013) as well as supported by the slightly lower bacterial count at 48 h in this study. In addition, end bacterial counts between 7.55 ± 0.08 and 8.63 ± 0.09 $\log_{10}$ CFU/g for different temperatures were consistent with the previous results. Microbial shelf lives were between 4 and 151 h and shorter than in the laboratory trials, presumably caused by the higher initial bacterial load. These results indicate the difficulty of varying initial bacterial counts.

Table 4.2. Remaining shelf lives at different measurement points during the pilot study and during storage at different temperatures, calculated based on real-time app measurements

Investigation point of measurement	**Remaining shelf lives based on real-time app measurements and storage temperatures [h]**		
	4°C (Transport)		
Factory sale (t = 24 h)	226	226	226
	4°C	**7°C**	**10°C**
Arrival at the laboratory (t = 48 h)	189	75	38
Storage at the laboratory (t = 71 h)	169	49	16
(t = 94 h)		44	
(t = 143 h)	146	12	
(t = 191 h)	89		
(t = 239 h)	17		
Calculated shelf life [h]	256	154	87

Table 4.3. Microbial and sensory shelf lives of raw pork sausage (based on the modified Gompertz model) and TTI shelf life measured by app and colorimeter (based on the Logistics model) after transport and storage at the laboratory at different temperature scenarios

	Storage temperature scenario at the laboratory [°C]			
	2°C	**4°C**	**7°C**	**10°C**
Microbial shelf life [h]	496	300	184	130
Sensory shelf life [h]	408	293	172	132
Predicted TTI shelf life by app [h]	N/A	256	154	87
TTI shelf life based on app measurements [h]	501	242	127	103

As a result, calculating product shelf lives for the adjustment of dynamic shelf life models and estimating the initial TTI charging value for a reliable shelf life prediction can be challenging. Also, sensory evaluation showed shorter shelf lives compared than in the laboratory trials (Table 4.1), and sensory shelf lives at 2°C, 4°C and 7°C were slightly shorter than the microbiological shelf life. This observation is contrary to the results in the laboratory studies and may have batch-specific reasons, such as variations in color or texture caused by variations in the composition of the raw materials. It is also possible that the increased initial bacterial count of the product has an increased effect on sensory perception. The variations in microbiological and sensory shelf lives support the integration of a certain safety margin by adjusting the TTI charging time. The direct comparison of LAB growth on raw pork sausage and predicted and measured TTI color values by the app along the supply chain is shown in Figure 4.4a and 4.5a, exemplary for scenarios at 4°C and 10°C, respectively. Visual discoloration of TTIs during storage at 4°C and 10°C are shown in Figure 4.4b and 4.5b, respectively, with pictures taken by the app. The total microbial shelf lives of raw pork sausages stored at the different temperature scenarios based on the modified Gompertz model are shown in Table 4.3.

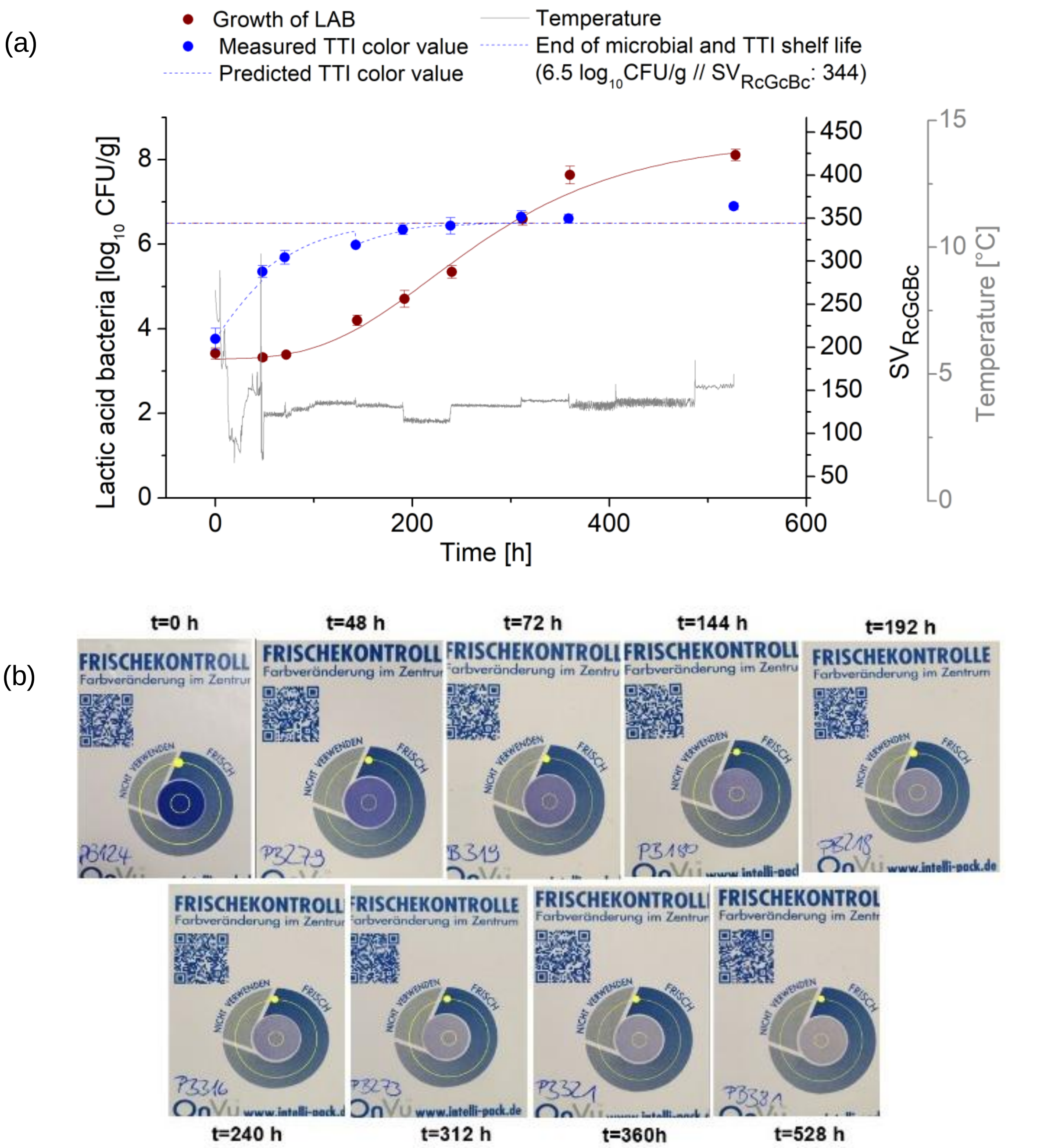

Figure 4.4. (a) Predicted and measured TTI color values by app and shelf lives of raw pork sausage during transport along the supply chain and storage at 4°C (n=8 per measuring point). (b) Visual discoloration of TTIs during storage at 4°C

The microbiological product shelf lives at 4°C, 7°C and 10°C were 30 to 43 h longer than those of the predicted TTI shelf lives based on app measurements. Shelf lives at 2°C could not be compared, since no TTI shelf life could be predicted by app measurements, as described above. Taoukis et al. (1999) specifies a difference of less than 24 h between shelf the lives of products and TTI as acceptable.

(a)

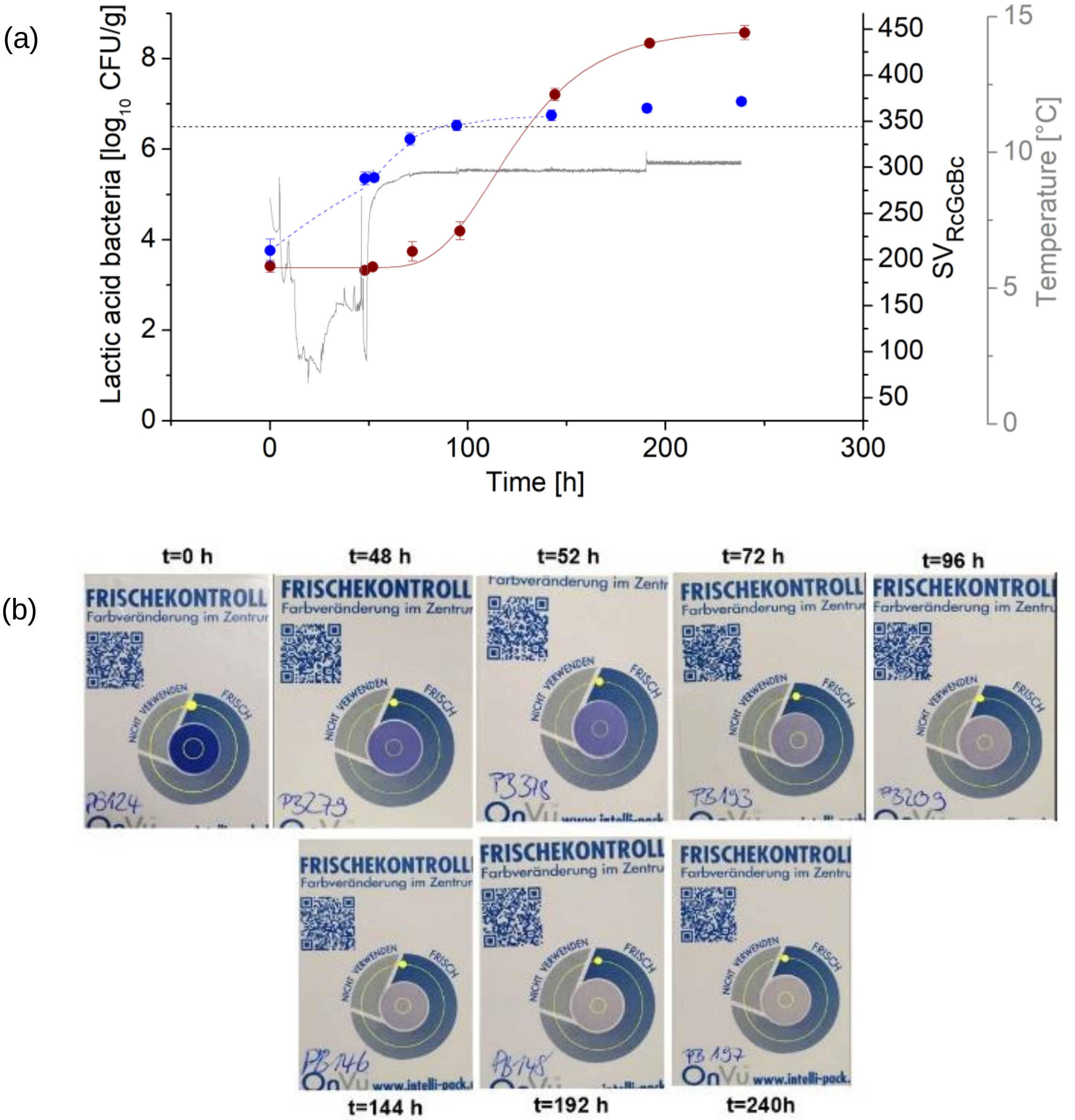

Figure 4.5. Predicted and measured TTI color values by app and shelf lives of raw pork sausage during transport along the supply chain and storage at 10°C (n=8 per measuring point). (b) Visual discoloration of TTIs during storage at 10°C

However, during the analysis of variances, it became clear that the differences are caused by systematic errors. Even if the initial TTI charging value had been adjusted to the shelf life of raw pork sausage at 4°C, conditions in practice led to higher variations. One reason may be the difference in humidity during the charging process in the higher pilot study compared to laboratory conditions. Kreyenschmidt, Christiansen, et al. (2010) observed longer discoloration times when humidity was high during charging. This finding enhances the importance of constant charging conditions. Variances in product and TTI shelf lives can be further eliminated by adjusting the TTI charging time; however, a certain safety margin of the TTI shelf life is useful to obtain product safety, especially regarding such a highly sensitive product as raw pork sausage.

The generally good agreement of the TTI kinetics reflected by app measurements and the product kinetics is shown in Figure 4.6, comparing raw pork sausage shelf lives and TTI shelf lives based on app measurements at the different storage temperatures. The shelf life differences between the product and TTI dependent on the storage temperature are proportional to each other. This reveals the suitability of the TTIs as a shelf life predictor for this specific and highly perishable product and confirms the useability of the app when systematic errors, as described above, were eliminated. The good correlation between the OnVu™ TTI discoloration and microbial spoilage was also shown in several studies investigating poultry and fish (Brizio & Prentice, 2014; Mai et al., 2011; Tsironi et al., 2011). The good agreement of the kinetics in this study showed that the TTI read-out by the app could also serve as a reliable freshness indicator, comparable to the read-out by a conventional colorimeter (Figure 4.6). Lee et al. (2019) also showed a good correlation between the spoilage parameters of chicken breast and discoloration of a freshness indicator as RGB values measured by smartphone.

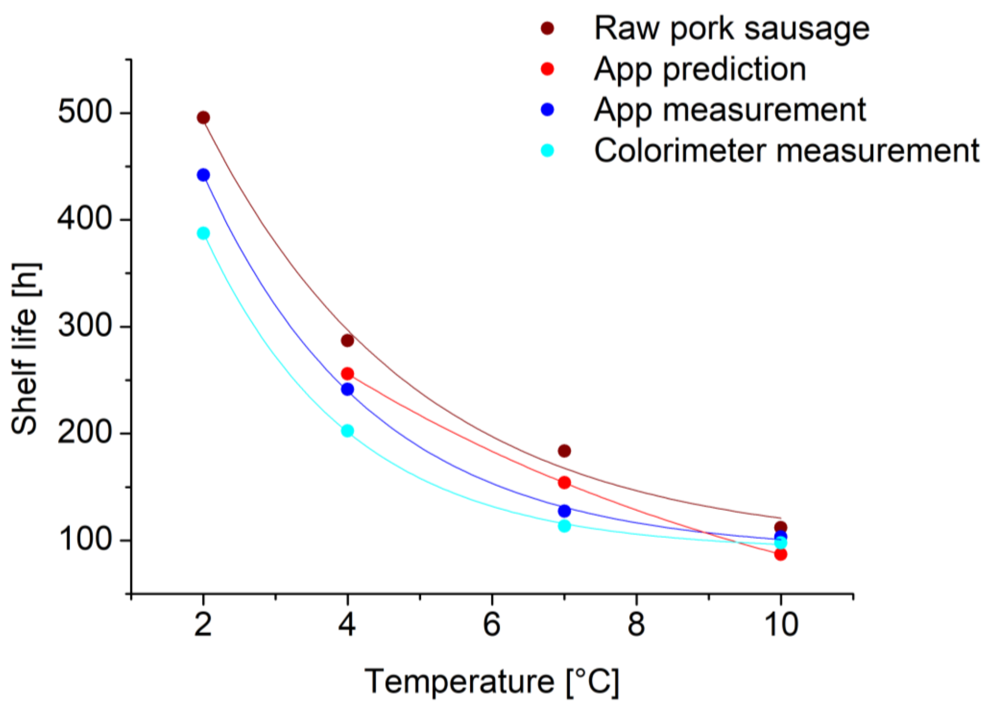

Figure 4.6. Microbial shelf lives of raw pork sausage, predicted and measured TTI shelf lives by app and TTI shelf lives measured by colorimeter at different storage temperatures in the pilot study (n=8 per measuring point)

The applicability of an app as a reliable shelf life tool enables all stakeholders, from the producer, retailer, to the final customer, to use an adequate temperature monitoring and shelf life predicting system. The app-based TTI system can function as an intelligent packaging tool to monitor and share data to support dynamic shelf life, and thus, lower food waste along the supply chain (Poyatos-Racionero et al., 2018; Verghese et al., 2015). Current information and data transfer almost require the adaptation of static expiry dates to dynamic shelf lives (Azeredo & Correa, 2021). The implementation of dynamic shelf life can thus lead to longstanding discussed Least Shelf Life First Out approaches (Koutsoumanis & Taoukis, 2005; Taoukis et al., 1999). The possibility of these strategies by sensor-based TTI systems was also shown by Qi et al. (2014).

Major challenges for the successful implementation remain the legal assessment of a dynamic shelf life based on real-time data and the legitimacy of an app system running on a standard smartphone as a reliable measurement device. In addition to the mandatory shelf life date according to Regulation No 1169/2011 on the European level (The European Parliament and the Council, 2011), the optional indication of a "concrete shelf life period" based on verifiable storage conditions measured by TTIs, should be forced through guidelines and policy recommendations as part of food waste reduction strategies, which is proposed by Simon (2021). Enforced legal requirements could have a similar positive effect as the introduction of the HACCP concept, which was initially rejected by the companies but is now fully implemented (Lee & Rahman, 2014). The application of intelligent packaging is essential for increasing resource efficiency along the supply chain, not least because of the rising awareness and demand of consumers for sustainable packaging and safer foods (Korte et al., 2021).

4.5 Conclusion

The study showed the application of a novel app-based TTI system used to the remaining shelf lives of raw pork sausage along a typical supply chain, including transport and storage at temperature conditions as they occur in practice. The results revealed that microbial growth kinetics of raw pork sausage are in good correlation with the TTI kinetics measured by the app. Results further indicated that implementing an app-based shelf life prediction system is, in general, possible and can serve as a valuable monitoring tool for all stakeholders along the supply chain. This observation offers the possibility of preventing food waste in the highly sensitive and energy-intensive sector of raw meat, thus, saving environmental resources and making the supply chain more sustainable. The study also revealed the need for further developments, i.e., the adaptation of the shelf life prediction to low-temperature supply chains and an increase in the model's accuracy to reduce shelf life variances. Thus, practical data are needed to enable a more accurate and reliable app-based system. In the future, dynamic shelf life prediction based on app-measurements must be further investigated to use it as a helpful strategy to reduce food waste and make the supply chain more efficient. This requires both the implementation of legal framework conditions and the willingness of stakeholders, including consumers, to use such systems.

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5 Implementation of a time-temperature-indicator as a shelf life predictive tool for a ready-to-eat salad

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5.1 Abstract

Dynamic shelf life of a food product is a promising tool for reducing food waste. Time-temperature-indicators (TTIs) for continuous temperature monitoring and shelf life models of perishable products, such as ready-to-eat (RTE) salads, can serve as a basis for such developments. Supply chains can be simplified using digitalized TTI read-out systems. This study tested a novel app system for the digital read-out of OnVu™ TTIs for a RTE salad under laboratory and real supply chain conditions. The RTE salad, consisting of green lettuce, corn, and sliced carrots, was first analyzed to define microbial spoilage kinetics. The data were combined with a predictive model for the OnVu™ TTI, and the shelf life prediction of the RTE salad based on app measurements was validated in laboratory and real-life pilot studies. Sliced carrots were identified as the shelf-life-limiting component and, thus, selected as the basis for modeling. The spoilage kinetics analysis revealed an activation energy of 23.15 kcal/mol, consistent with the activation energy of the TTI. Laboratory analysis showed high accordance between the predicted shelf life by TTI (183 h) and the product shelf life (182 h) at 4°C, however, also high variations in a dynamic temperature scenario due to differences in initial bacterial counts. . Pilot studies showed that the TTI shelf lives were shorter than product shelf lives at storage temperatures of 2°C – 217 h for TTI and 261 h for product – and 7°C – 89 h for TTI and 130 h for product – due to unexpectedly faster discoloration. Charging conditions in practice and model improvements can help optimize the process. Nevertheless, the predicted TTI and product shelf lives had generally consistent kinetics, revealing that eliminating systematic errors could help improve the reliability of the app-based system.

5.2 Introduction

Static date labels and inadequate knowledge about shelf life lead to avoidable food waste (Aschemann-Witzel et al., 2015; Chakravarthi & Ghosh, 2023; Chan, 2022; Kavanaugh & Quinlan, 2020; Schanes et al., 2018). Labeling the shelf life of chilled goods is mostly combined with maintaining a maximum storage temperature. If the product is handled properly or stored at a lower temperature, it is often still high-quality and safe even after the expiration date for the labeled shelf life. On the contrary, if a product's storage temperature is inappropriate, the product can spoil sooner. As a result, the idea of a dynamic shelf life has emerged to address the need for flexibility in these circumstances.

Dynamic shelf life is based on the knowledge about the spoilage kinetics of a product, which is used to build a predictive model for calculating the actual shelf life in combination with real-time temperature data (Albrecht et al., 2021; Corradini, 2018; Tromp et al., 2012). Based on real supply chain conditions, products with an extended shelf life can still be sold and consumed, whereas products with a shortened shelf life need to be sold and consumed sooner. With dynamic pricing strategies, dynamic shelf life can serve as an effective tool for reducing food waste (Buisman et al., 2019). For shelf life modeling, it is necessary to control the temperature conditions along the supply chain to ensure reliable prediction and give the consumers confidence in the shelf life of perishable products. Monitoring tools, such as time-temperature-indicators (TTI), combined with predictive shelf life modeling, can be used to control temperature conditions from production to consumption. These tools can help indicate the actual product status by color changes (Albrecht et al., 2020). TTIs are mainly designed for and tested on animal-based products, as they are most susceptible to temperature changes (Poyatos-Racionero et al., 2018). Current research examines the combination of TTI and product using predictive shelf life modeling and different principles of function. For instance, Giannoglou et al. (2019) investigated enzymatic TTIs for the shelf life monitoring of various smoked fish products. Pawde et al. (2023) showed that the color change of a paper-based TTI is able to reflect shelf life of pasteurized milk based on spoilage kinetics. The application of the OnVu™ TTI in a fresh poultry supply chain was analyzed by Albrecht et al. (2020), showing that a monitoring software tool based on predictive modeling can support supply chain processes. All studies have in common that for investigating the applicability of TTIs, an accurate examination of the product’s kinetics is crucial to develop reliable predictive models. Focus in research is mainly laid on meat, meat products, fish, and dairy. Also, the spoilage of plant-based products is highly temperature-dependent. For example, fresh-cut vegetables, or ready-to-eat (RTE) salads, are intensely processed, with extensive shredding and slicing; this process promotes water loss and microbial spoilage (Barry-Ryan & O'Beirne, 1998; García-Gimeno & Zurera-Cosano, 1997; Ragaert et al., 2007). Additionally, RTE salads and mixed products already have aerobic mesophilic counts of around log 6 CFU/g after packaging and on the day of purchase (Łepecka et al., 2022; Schillinger & Becker, 2007; Tsironi et al., 2017). Because of microbial growth and a high dependence on storage temperature, the shelf life of RTE salad is thus particularly limited.

Even if the transport requirements of chilled products are maintained, temperature fluctuations in the RTE salad supply chain during the transport, loading, and storage at the retail store and, finally, the consumer can significantly affect microbial growth and, hence, the product shelf life (McKellar et al., 2014; Nunes et al., 2009; Rediers et al., 2009). Therefore, continuous temperature monitoring by TTIs helps maintain product safety and calculate real-time shelf lives, with a detailed knowledge of spoilage kinetics as the basis for dynamic modeling. Stakeholders are, in general, aware of the benefit of intelligent packaging systems (Cammarelle et al., 2021; Tiekstra et al., 2021); however, most of the producers, logisticians, and retailers are still using only conventional temperature monitoring systems for mandatory controls with no additional smart technologies (Waldhans et al., 2024).

Digitalizing the TTI read-out process with smartphones can facilitate the management and workflow of this monitoring system along the chain, optimizing supply chain processes and saving more resources. Also, digitalized information about the temperature history and actual product shelf life can improve consumer confidence and help reduce food waste due to an extended shelf life or consumption before spoilage. There have been developments in this field (Albrecht et al., 2020; Waldhans et al., 2024; Waldhans et al., 2023). Such systems need to be investigated in practice to validate their applicability as a reliable tool for temperature monitoring and shelf life prediction in RTE salad supply chains. Therefore, this study aimed to test the newly developed app-based read-out system for the OnVu™ TTIs described by Waldhans et al. (2023) for the shelf life prediction of an RTE salad. Therefore, a shelf life model of the RTE salad was developed based on laboratory storage tests under different constant and dynamic temperature conditions. Based on the product-specific shelf life model and the TTI shelf life model (chapter 4), the TTI read-out by app and shelf life prediction was validated in a German supply chain for the RTE salad from production to consumption.

5.3 Materials and methods

5.3.1 Sample specification and experimental design

The product to be examined was a vegan RTE salad (200 g per package) consisting of four components: lettuce (47 %, in variable proportions by weight: white cabbage, endive, frisée, lollo bionda, lollo rosso, and radicchio) with tomatoes (28 %), sliced carrots (11 %), and corn (14 %). The shelf life was determined for 120 h at a maximum of 7°C. The components were placed in separate compartments inside the packaging and sealed under the normal atmosphere. An herbal vinaigrette (100 g) was separately included and not considered for the tests.

A series of experiments was conducted. A scheme of the consecutive studies is shown in Figure 5.1. First, the spoilage kinetics of the RTE salad were investigated under laboratory conditions. Samples of the product components were stored under different static temperature conditions to obtain quality parameters. The determined shelf-life-limiting spoilage parameter was used to develop the shelf life model for the RTE salad. Then, the model was validated in a subsequent laboratory storage experiment at dynamic storage temperatures. Next, based on the product shelf life model and a likewise validated dynamic TTI model of the OnVu™ TTIs (according to chapter 4), the TTI read-out system with an app and the shelf life prediction of the product were validated. Therefore, pilot studies were conducted under laboratory and real supply chain conditions. In the laboratory study, product samples equipped with TTIs were stored at one static and one dynamic temperature scenario. In the supply chain study, samples with TTIs were transported along the supply chain to the laboratory, including two transshipment points and the retail store. The temperatures along the chain were measured to assess the conditions, potential fluctuations, and weak points. In the laboratory study, storage conditions at the consumer were simulated by storing the samples at three different temperature scenarios. The accuracy of the shelf life prediction by the app was tested in both studies.

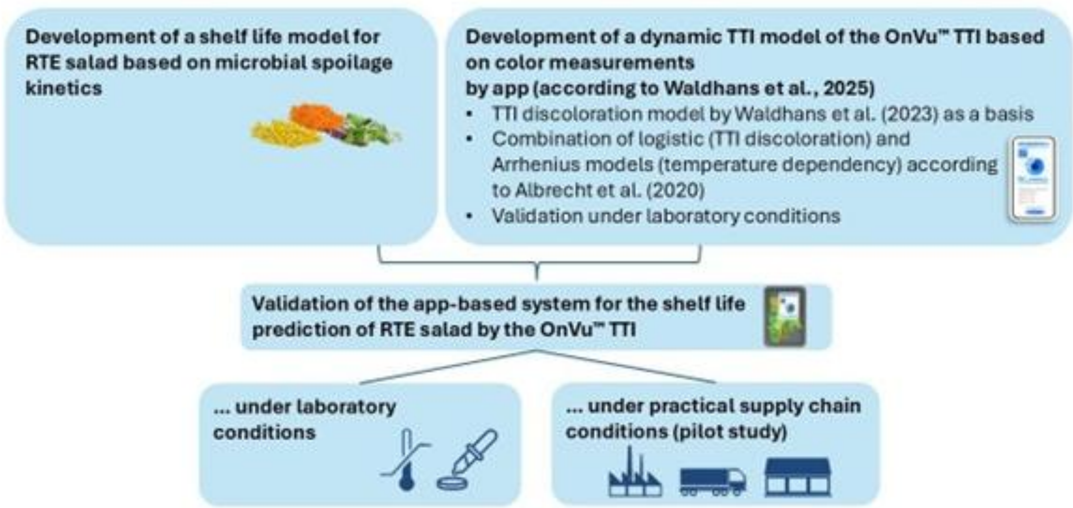

Figure 5.1. Overview of the consecutive experiments performed in this study

5.3.2 Development of a kinetic shelf life model for the RTE salad

5.3.2.1 Shelf life investigation of the RTE salad

The shelf life model for the described RTE salad was developed based on microbial growth kinetics. Therefore, laboratory storage experiments were conducted at five different constant temperatures (2°C, 4°C, 7°C, 10°C, and 15°C) to characterize the spoilage kinetics and quality loss. A dynamic temperature scenario with shifts at the beginning of microbial growth (shifting to 15°C for 4 h at 26, 48, and 72 h after production) was conducted to validate the shelf life prediction model under simulated temperature fluctuations. Product samples arrived at the laboratory 24 h after production, and microbial, sensory, and other determined quality parameters were investigated immediately and at defined time points according to the storage temperatures.

For microbial analysis, the three components of the RTE salad, mixed lettuce, sliced carrots, and corn, were investigated separately to identify the shelf-life-limiting component. The tomatoes, packed as a whole, were not considered for the shelf life assessment, as they are not as prone to microbial spoilage as the other components. Representative samples of a particular component, mixed lettuce (25 g), sliced carrots (10 g), and corn (10 g), were extracted from each package; a smaller quantity of carrots and corn was obtained due to their smaller quantities in the package. Each sample was transferred to a filtered stomacher bag filled with 225 g of saline tryptone diluent (0.85 % NaCl, Oxoid GmbH, Basingstoke, United Kingdom) and 90 g of 0.1 % tryptone (VWR International GmbH, Darmstadt, Germany) to achieve a tenfold dilution and homogenized in a stomacher 400 (Kleinfeld Labortechnik, Gehrden, Germany) for 60 s. Next, a tenfold dilution series was prepared using the saline tryptone diluent. The growth of the total viable count (TVC) and spoilage organisms were investigated by transferring appropriate dilutions of the culture suspension onto the growth media in different Petri dishes in duplicates. TVC was determined by the pour plate technique using plate count agar (Merck KGaA, Darmstadt, Germany) and incubation at 30°C for 72 h. Lactic acid bacteria (LAB) were likewise identified by the pour plate technique using the De Man-Rogosa-Sharpe agar (Merck KGaA, Darmstadt, Germany) and incubation at 37°C for 72 h. *Pseudomonas* spp., as well as yeasts and molds, were detected using the spread-plate technique on the Pseudomonas CFC agar base (Merck KGaA, Darmstadt, Germany) supplemented with glycerol and CFC selective supplement (Merck KGaA, Darmstadt, Germany) and yeast extract glucose chloramphenicol agar (YGC) (Merck KGgA, Darmstadt, Germany), respectively. CFC samples were incubated at 25°C for 48 h and YGC samples at 25°C for 120 h. Enterobacteriaceae were investigated by the pour plate technique with overlayed violet red bile dextrose agar (Merck KGaA, Darmstadt, Germany) and incubation at 37°C for 24 h. Microbial counts were quantified and calculated as $\log_{10}$ CFU/g. The end of shelf life was reached at a microbial count of 7.5 $\log_{10}$ CFU/g for TVC, as specified by the guidelines of the German Society for Hygiene and Microbiology (DGHM).

Microbial analyses were accompanied by a sensory evaluation of the RTE salad components by a trained panel of three to four participants to uncover the differences in objective microbial spoilage and subjective perception. The color, odor, and texture of each mixed lettuce, sliced carrots, and corn were evaluated using a 5-point scale (5 as the highest quality and 1 as the lowest) with determined characteristics for each point and attribute. The scheme of the sensory evaluation is shown in the Appendix (Table A.2.1). A sensory index (SI) was calculated using equation 5.1 for each component:

$$SI = \frac{C + 2 * O + 2 * T}{5} \tag{5.1}$$

where SI: sensory index at time [h]; C: evaluation of color; O: evaluation of odor; T: evaluation of texture. The endpoint of the sensory shelf life was set at SI = 2.8.

The investigation of the gas atmosphere in the package and the pH value and color as additional quality parameters were conducted in parallel. They were not considered for the shelf life model as microbial spoilage showed a significantly higher temperature-dependent effect.

5.3.2.2 Analysis and modeling of the shelf life data of RTE salad

The microbial growth and sensory evaluation data were fitted using the statistical software OriginPro 8.0G (OriginLab Corp., Northampton, MA, USA). Primary and secondary models were used to fit the microbial data, according to Bruckner et al. (2013). Microbial growth as a function of time was described by the modified Gompertz model on the primary level (Gibson et al., 1987):

$$N_t = N_0 + a * e^{-e^{-k*(t-xc)}} \tag{5.2}$$

where N_t: microbial count [$\log_{10}$ CFU/g] per time t [h]; N_0: lower asymptotic line of the growth curve/the initial bacterial count [$\log_{10}$ CFU/g]; a: amplitude (difference between the upper asymptotic line of the growth curve/the maximum bacterial count N_{max} [$\log_{10}$ CFU/g] and N_0); k: relative growth rate at time [h^{-1}]; xc: reversal point (time at which maximum growth rate is obtained) [h]; t: time [h].

The temperature dependency of microbial growth was assessed using the Arrhenius approach on the secondary level, as calculated using the following equation:

$$\ln(k) = \ln(k_0) - \frac{E_a}{R} \cdot \frac{1}{T} \tag{5.3}$$

where k: reaction rate [h^{-1}]; k_0: constant [h^{-1}]; E_a: activation energy [kJ mol^{-1}], R: ideal gas constant [8.314 J mol^{-1} K^{-1}]; T: absolute temperature [K].

Then, models were used to conduct shelf life prediction under fluctuating temperatures, according to Kreyenschmidt, Hübner, et al. (2010) and Bruckner et al. (2013). Therefore, the values of N_0 at 4.29 $\log_{10}$ CFU/g and N_{max} at 8.26 $\log_{10}$ CFU/g were used to calculate the average initial and maximum TVC counts, respectively, for sliced carrots at constant temperatures. Based on those data, the amplitude was calculated and added to the model. For each temperature interval during the dynamic scenario, the reversal point xc was calculated based on the current bacterial count and the temperature. The initial xc was calculated based on the exponential regression of xc against temperature under isothermal conditions (chapter 4). The relative growth rate k of the interval was calculated based on the Arrhenius model and the temperature. Based on these parameters, the bacterial count and the reversal point for each interval were calculated.

The model's performance was validated according to Ross (1996) by calculating the bias and accuracy factor with the following equations. In contrast to the bias factor, the accuracy factor is more meaningful because it does not relativize the underestimation and overestimation of the bacterial count.

$$B_f = 10^{\left(\sum \log\left(\frac{predicted_i}{observed_i}\right)/n\right)} \tag{5.4}$$

$$A_f = 10^{\left(\sum \left|\log\left(\frac{predicted_i}{observed_i}\right)\right|/n\right)} \tag{5.5}$$

where B_f: bias factor; A_f: accuracy factor; $predicted_i$: predicted bacterial growth values; $observed_i$: observed bacterial growth values; n: number of observations and where B_f = 1.00 indicates an exact agreement between the predicted and observed values; B_f >1.00 or B_f <1.00 indicates that the model overestimates or underestimates bacterial growth, respectively ("fail-safe" or "fail dangerous" model); A_f = 1.00 indicates an exact agreement of the predicted and observed growth.

5.3.3 Validation of the app-based system for the OnVu™ TTIs for the shelf life prediction of RTE salad

5.3.3.1 Validation under laboratory conditions

First, the app-based read-out system for OnVu™ TTIs (Waldhans et al., 2023) was tested for the shelf life prediction of the RTE salad under laboratory conditions. The basic OnVu™ TTI labels in the non-activated state (Batch 21.06.2021, Color Batch 00552HN8, Ciba Specialty Chemicals & Freshpoint, Basel, Switzerland, patent WO/2006/048412) were provided by BIZERBA Labels & Consumables GmbH. The labels were activated by a UV light charger (GLP 80/56 TTI, Bizerba, Germany) under chilled temperature conditions in the laboratory, which automatically applied a UV filter (LOT#146 000018272) on the label for protection after activation. The charging time can be individually adapted according to the desired initial color value and discoloration length based on the product's shelf life. The TTI shelf life model based on color measurements by app and its laboratory validation has already been described (chapter 4). The shelf life model was used to predict the remaining shelf life of the TTIs based on the measured TTI values by the app along the supply chain.

Two laboratory studies were conducted, one at static and one at dynamic temperature conditions. Namely, 30 RTE salad samples were equipped with OnVu™ TTIs immediately after arrival at the laboratory (t = 24 h) in each study. The TTIs were activated according to Albrecht et al. (2020) under chilled temperature conditions with appropriate charging times and fixed on single packaging units. Then, two layers of self-adhesive white paper were applied to the packaging lid to create a unique measurement subsurface. Samples were stored at 4°C in one study and at a dynamic scenario in the other study (48 h at 4°C, 48 h at 7°C, and 10°C until the end of storage) in high-precision low-temperature incubators (MIR 153, SANYO Electric Co., Ora-Gun, Gumma, Japan). The storage temperature was monitored every 5 min by data loggers (Testo SE & Co. KGaA, Titisee-Neustadt, Germany). TTI discoloration was measured by the app according to Waldhans et al. (2023) at defined time points using a Nokia smartphone 7.2 Dual-SIM Android™ 9.0 48m pixels (Nokia Oyj, Espoo, Finland). The color measurements by the smartphone were made in a dark room with a fixed smartphone holder. A standardized measuring method was conducted, using a 2x zoom and illumination by a daylight lamp (1620 Lm, 6500 K, Tageslichtlampen24.de, Kiel, Germany). Reference TTI measurements by a colorimeter were conducted in parallel at all investigation points using the EyeOne i1 Basic Pro1 (X-rite; Gretag Macbeth, Regensdorf, Switzerland). Also, microbial and sensory investigations of the RTE samples were performed, and five samples were analyzed at each time point. The growth of TVC on sliced carrots was investigated as a potential predictor for the shelf life modeling of the food product. Besides, microbial spectrum, sensory, and relevant quality parameters were analyzed. Data analysis and modeling were likewise conducted.

5.3.3.2 Validation under practical supply chain conditions

An overview of the validation under practical supply chain conditions and its respective steps and measurement points is shown (Figure 5.2). A total of 200 single packaging units of RTE salad were equipped with OnVu™ TTI labels immediately after the packaging process at the factory; they were attached to the samples. Every four single-package units were placed in an open cardboard box; consequently, 50 boxes were packed and positioned on one pallet. The temperature conditions during transport were monitored every 5 min by data loggers positioned in the cardboard boxes on the pallet. The pallet was transported in an actively cooled truck to the laboratory via two transshipment points and a retail store. After arrival at the laboratory, the sample packages were stored in high-precision, low-temperature incubators (MIR 153, SANYO Electric Co., Ora-Gun, Gumma, Japan) at 2°C and 7°C. After 48 h, some of the samples stored at 7°C were moved at 10°C to simulate a higher storage temperature at the hands of the consumer. The temperature was monitored every 5 min during transport and storage (iButton DS1922L Thermochron Data Logger, Maxim Integrated, San Jose, CA, USA; Testo SE & Co. KGaA, Titisee-Neustadt, Germany).

TTI discoloration was measured as described for the laboratory pilot studies. Color measurements by the app in the factory (initial point) were performed free-handed, and laboratory measurements were made in the darkroom. In all settings, the standardized measuring method was conducted. Reference TTI measurements by colorimeter were parallelly conducted at all investigation points. Microbial and sensory investigations of the samples (n = 8) were conducted at the determined measurement points, including the entire set of parameters described above. Data analysis and modeling were likewise conducted.

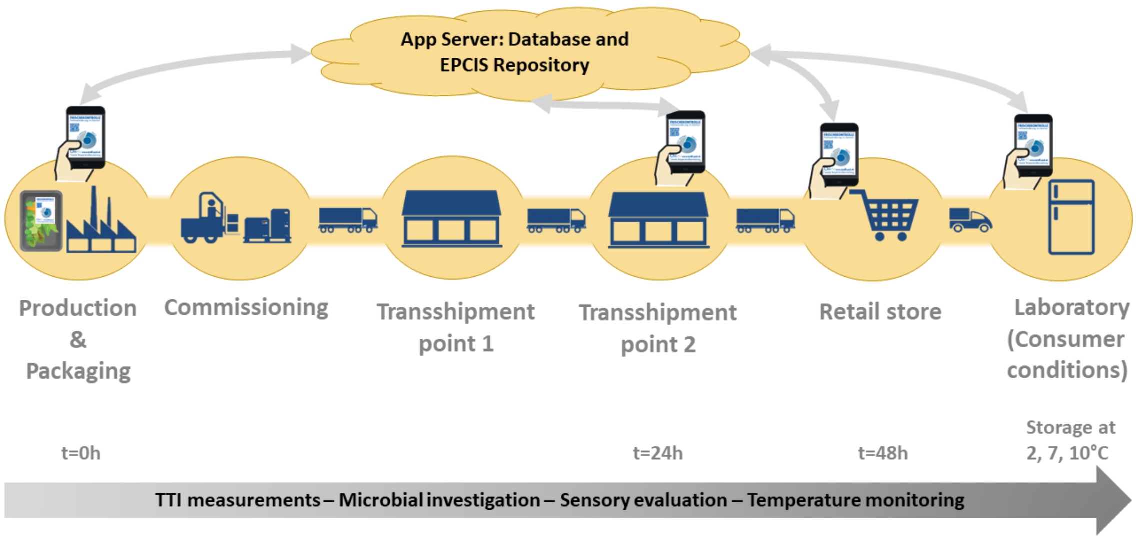

Figure 5.2. Illustration of the pilot study with its consecutive steps along the supply chain from RTE salad production to laboratory storage and points for TTI measurements, microbial investigation, sensory evaluation of the product, and temperature monitoring

5.3.3.3 Analysis and modeling of TTI shelf life data

Modeling of the discoloration kinetics of the app-measured TTIs, as well as the calculation of the remaining shelf life, was conducted (Waldhans et al., 2023; chapter 4). Based on the detected RGB values by the app for the blue dot of the TTIs corrected by white balance, square values were built and modeled using the kinetic approach by Taoukis & Labuza (1989) and Tsironi et al. (2008). The LAB color data detected by the colorimeter was calculated likewise. The discoloration data were then described by the logistic model (Albrecht et al., 2020; Kreyenschmidt, Christiansen, et al., 2010).

$$SV_{LAB;\, R_cG_cB_c} = \frac{a}{1 + e^{-k(t-xc)}} \tag{5.6}$$

where a: amplitude; k: reaction rate (h^{-1}); xc: reversal point (h); t: time (h) for each logistic model in CIELAB and RGB color systems.

The dynamic TTI model based on app measurements (chapter 4) was used; initially, it was adapted to the TTI charging conditions in this study. Additionally, the model was adjusted to provide improved accuracy; therefore, the temperature dependency of the amplitude a was described by an exponential regression based on the results for a at different charging times and temperatures. Based on the color values in the studies and the TTI shelf life model, the remaining TTI shelf life at selected time points was calculated

(Albrecht et al., 2020). The discoloration points and, therefore, the end of shelf life points were determined as SV_{RcGcBc} = 344 for the TTI shelf life calculation in the RGB color system (Waldhans et al., 2023) and SV_{LAB} = 71 in the CIELAB color system (Kreyenschmidt, Christiansen, et al., 2010).

5.4 Results and discussion

5.4.1 Development of a kinetic shelf life model for RTE salad

All components (mixed lettuce, corn, and sliced carrots) had high initial bacterial counts in all investigations at the constant temperatures of 2°C to 15°C. For sliced carrots, bacterial counts (TVC) at 24 h after production ranged from 4.16 ± 0.28 to 5.20 ± 0.16 $\log_{10}$ CFU/g. Mixed lettuce and corn had initial TVC values of 4.43 ± 0.47 to 5.34 ± 0.45 $\log_{10}$ CFU/g and 3.47 ± 0.34 to 4.96 ± 0.63 $\log_{10}$ CFU/g, respectively. These results were highly consistent with those in many studies that reported high microbiological loads for RTE and fresh-cut salads (Tsironi et al., 2017; Xylia et al., 2021) and, consequently, very short shelf lives. As a result, sliced carrots were identified as the product component with the shortest microbial shelf life, even at low temperatures, in nearly all experiments. The shelf lives based on the respective models for all three components at the different storage temperatures were calculated (Table 5.1). For every product component in the RTE salad, no specific spoilage organism could be identified, as all investigated microorganisms showed a high growth, and no dominating organism could be identified. This finding can be explained by the generally broad microbial diversity on vegetables due to farming practices and their growth near the ground (Gorni et al., 2015; Leff & Fierer, 2013).

Therefore, the shelf life modeling of the RTE salad was focused on sliced carrots and was constructed based on the growth of TVC. Model parameters of the Gompertz model for the microbial growth and of the linear model for the Sensory Index are shown in the Appendix (Table A.2.2). Especially at low temperatures, the microbial shelf life of sliced carrots was significantly shorter than those of mixed lettuce and corn. Also, the sensory evaluation revealed that sliced carrots had the shortest shelf life (Table 5.1). The sensory shelf lives of all components showed a significantly longer shelf life than those deduced from microbial analysis. The differences between microbial and sensory shelf lives indicate that the freshness of RTE salad can not be easily assessed visually. In contrast, Condurso et al. (2020) reported shorter sensory shelf lives of julienned carrots than microbial shelf lives. Also, Piagentini et al., (2005) modeled the shelf life of fresh-cut leafy vegetables based on sensory changes. However, according to the reference value of the DGHM guidelines, the results from this study identify microbial growth as the main factor for spoilage. Similarly, Calonico et al. (2019) and Arienzo et al. (2020) confirm the high microbial load and fast spoilage of RTE salads along the supply chain, supporting the use of adequate spoilage and temperature monitoring to ensure food safety.

Table 5.1. Calculated microbial shelf lives (based on the growth of TVC) and sensory shelf lives of separately investigated RTE salad components mixed lettuce, corn, and sliced carrots dependent on the storage at different constant temperatures. (n=3). Shortest microbial and sensory shelf life for each temperature is shown in bold.

	Microbial and sensory shelf lives of the components [h]					
Temperature [°C]	**Mixed lettuce** 		**Corn** 		**Sliced carrots** 	
	Shelf life [h]					
	Microbial	**Sensory**	**Microbial**	**Sensory**	**Microbial**	**Sensory**
2	411	556	398	**425**	**241**	525
4	375	493	252	408	**196**	**321**
7	153	246	**132**	234	139	**231**
10	105	217	87	236	**82**	**140**
15	82	100	73	95	**61**	**91**

The growth of TVC on sliced carrots at constant temperature conditions of 2°C to 15°C was modeled using a modified Gompertz model (Figure 5.3a). An activation energy (E_a) of 23.15 kcal/mol was calculated for sliced carrots based on the Arrhenius equation (Figure 5.3b), indicating that a reflection of the spoilage process is possible by the OnVu™ TTIs with 24.25 to 27.41 kcal/mol (Waldhans et al., 2023), as the difference between the activation energies is less than 5 kcal/mol (Taoukis et al., 1999). This finding provides the prerequisite for using the TTIs for shelf life prediction. In comparison, the E_a values described in other studies are lower, with 16.5 kcal/mol for the growth of *Pseudomonas* spp. on RTE leaf lettuce salad (Tsironi et al., 2017), 15.7 to 17.0 kcal/mol for different fresh-cut lettuce based on sensory data (Piagentini et al., 2005), and 11.06 to 17.13 kcal/mol for minimally processed fruits (Adiani et al., 2021). In addition, an E_a of 25.2 kcal/mol was described for RTE food (Haouet et al., 2018).

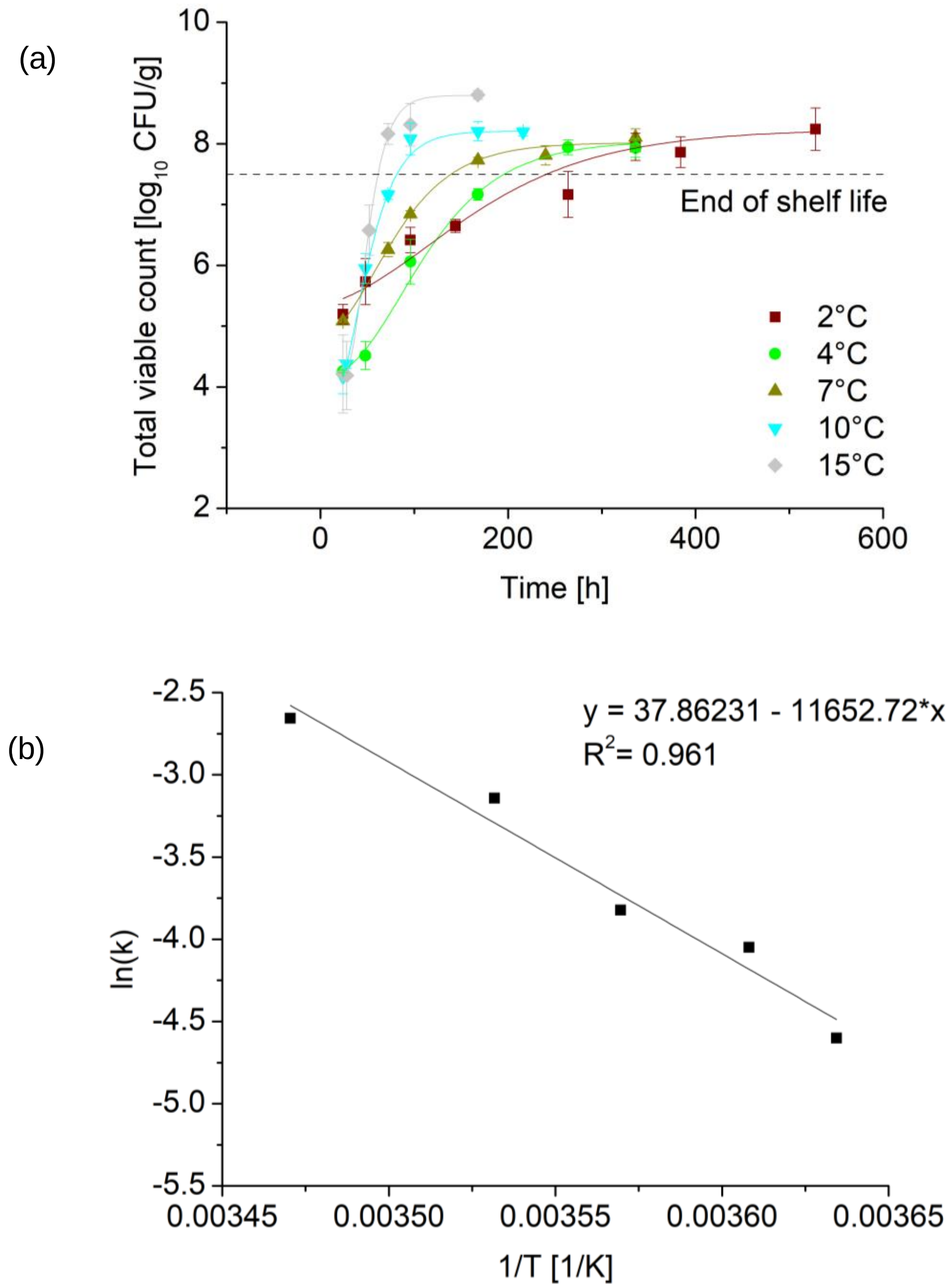

Figure 5.3. (a) Microbial growth of the TVC on sliced carrots at different constant temperatures modeled by a modified Gompertz model on the primary level. (b) Temperature dependency of the relative growth rate k of TVC growth on sliced carrots modeled by the Arrhenius equation on the secondary model level. (n = 3 at each investigation point*)*

The performance evaluation of the shelf life model, as tested by the dynamic temperature scenario, revealed a good accordance between observed and predicted values of TVC growth on sliced carrots ($R^2 = 0.948$). Model quality parameters were calculated with 1.00 for the bias factor and 1.04 for the accuracy factor, revealing that the model's prediction varied by 4 % from the actual observed TVC growth. The predicted and observed shelf lives differed slightly at 134 h and 143 h, respectively. The slight underestimation of the shelf life can benefit highly perishable products by providing a safety margin. Overall, these data suggest that the developed model provides reliable shelf life calculation under fluctuating temperature conditions.

5.4.2 Validation of the app-based system for the shelf life prediction of RTE salad by the OnVu™ TTI

5.4.2.1 Validation under laboratory conditions

The controlled laboratory charging procedure of TTIs for both the static and dynamic temperature experiments resulted in initial SV_{RcGcBc} values of 221.99 ± 5.05 and 227.25 ± 3.56, respectively. These data indicate low variations, a stable charging process, and fulfillment of the process. The initial bacterial counts on sliced carrots in the static temperature experiment were 4.50 ± 0.34 $\log_{10}$ CFU/g, consistent with previous results and indicating the accuracy of the shelf life model. Then, the predicted color values of the TTIs, the real-time TTI values as measured by the app, and TVC growth on sliced carrots at 4°C were compared; the results suggested an accordance between both kinetics based on the individual model parameters (Figure 5.4). The shelf life of the TTIs based on app measurements was calculated to be 183 h, and the bacterial growth kinetics inferred a shelf life of 182 h. Thus, the experiment demonstrated a high correlation between the kinetics and the suitability of the shelf life prediction by the app for sliced carrots.

The results from the scenarios under dynamic temperature conditions revealed remarkably different results. Sliced carrots were already highly contaminated at the beginning of the experiment with an initial TVC of 6.42 ± 0.32 $\log_{10}$ CFU/g, which resulted in a shelf life of only 64 h, thus, the product was spoiled even before the dynamic temperature settings began. Based on app measurements, the predicted TTI shelf life showed a shelf life of 124 h, which was inconsistent with the product shelf life. The initial charging of the TTIs was fitted to the expected shelf life of sliced carrots, and the prediction model was only applicable in the expected shelf life range. Therefore, the prediction did not work in this case. These results emphasize that product contamination can vary markedly and needs to be considered for future developments. For such cases, rapid methods for measuring the initial bacterial count of products would be helpful for adapting shelf life prediction for the actual product status (Kreyenschmidt & Ibald, 2012).

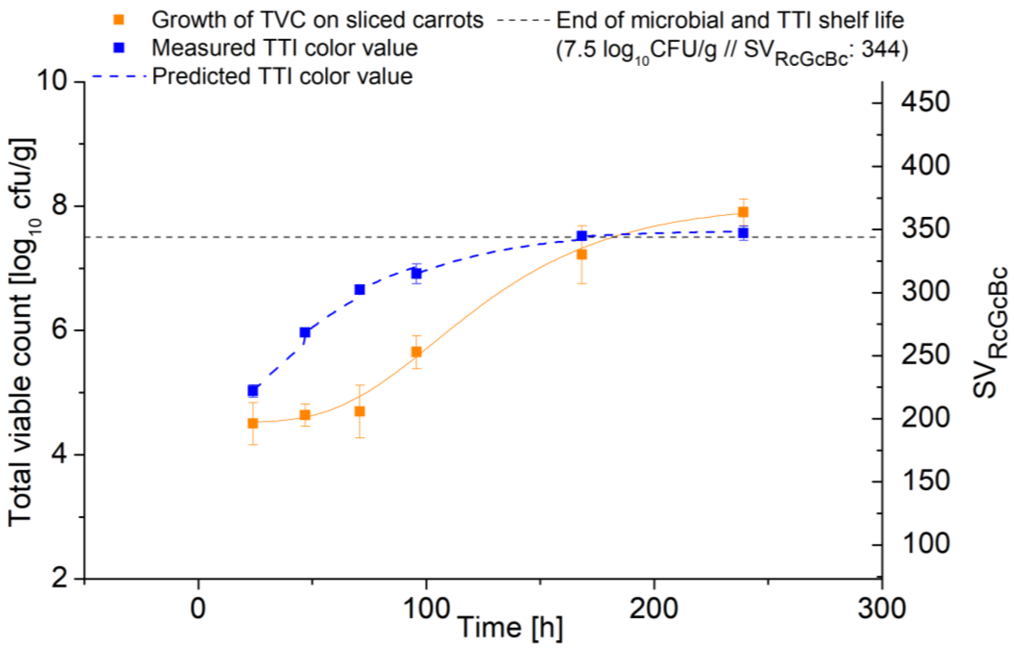

Figure 5.4. TTI color values both predicted and measured by the app compared to growth of TVC on sliced carrots during laboratory storage at 4°C (n = 5 at each investigation point)

5.4.2.2 Validation under practical supply chain conditions

The temperature conditions along the RTE salad supply chain from production to the retail store at different positions on the pallet were compared (Figure 5.5). The total mean temperature on the pallet was 2.8°C ± 1.7, indicating a generally well-maintained cold chain not exceeding the maximum storage temperature of 7°C. Temperature differences of up to 10.1°C could be revealed, indicating high variations influenced by the positions on the pallet and the exposure to the surrounding temperature. During the initial transport and storage at transshipment point 2, the samples on the upper layer were more exposed to the influence of the cooling unit, experiencing greater fluctuations as well as lower temperatures. Higher fluctuations on the upper level of the pallet were also observed by Rediers et al. (2009) in an endive salad supply chain. The temperature profiles also showed a relocation of the samples from transport to retail, as temperatures substantially decreased and fluctuated, likewise caused by proximity to a cooling unit. Meanwhile, temperatures as low as -2.4°C were measured; such low temperatures could lead to prolonged freezing and, thus, damage to the plant components. In this study, despite the adequate maintenance of the cold chain, the appearance of fluctuations suggests that continuous temperature control is useful, as fluctuations can even be greater, especially during transport in the summer. In addition, continuous temperature control can enhance consumers' trust in the cold chain, as they otherwise lack insights into the previous supply chain steps.

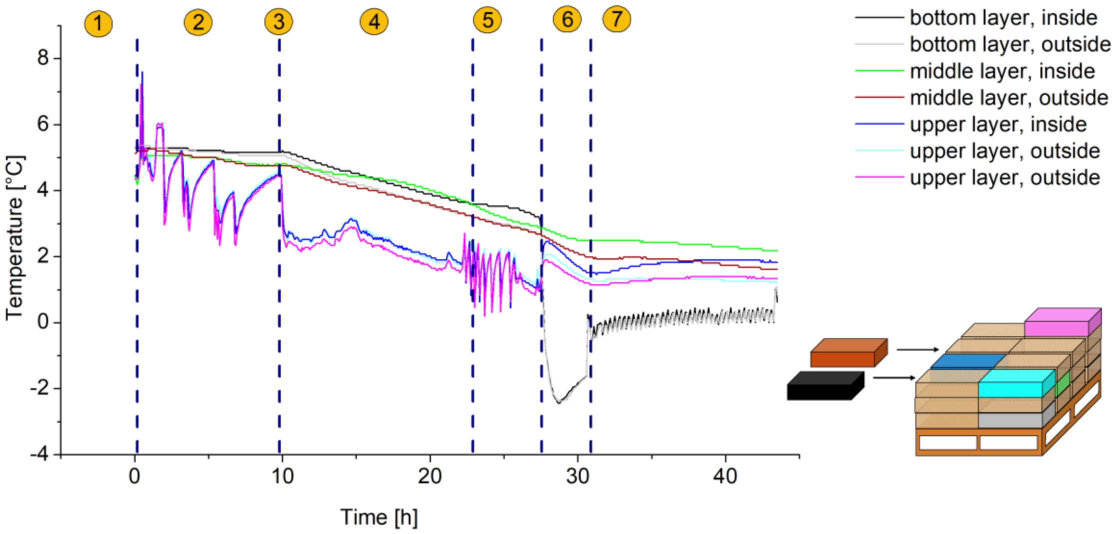

Figure 5.5. Temperature conditions during the pilot study measured on the pallet of RTE salad samples from production to storage in the laboratory. Consecutive steps of the supply chain: 1. Production and labeling. 2. Loading and transport. 3. Arrival at transshipment point 1. 4. Transport. 5. Arrival and storage at transshipment point 2. 6. Transport. 7. Arrival and storage at the retail store

The TTI charging process resulted in SV_{RcGcBc} values of 223.92 ± 14.79, as measured by the app, and SV_{LAB} values of 55.18 ± 0.25, as measured by the reference colorimeter for all samples (n = 200). The results were comparable with those in previous studies under practical conditions. The consistency in data shows that temperature conditions during the charging process are generally stable, and slight differences in the app measurements are caused by light variances. Thus, stable temperatures and standardized conditions are necessary but challenging for app measurements.

The calculated TTI shelf lives based on real-time app measurements along the supply chain steps at different temperatures were compared (Table 5.2). At transshipment point 1, no measurement point was included; therefore, no data were available. The remaining shelf lives for storage at 2°C were calculated at defined measurement points, yielding a total predicted shelf life of 217 h. The shelf life for storage at 7°C was predicted to be 89 h, based on real-time TTI data. The predicted shelf life for the third scenario with the temperature shift to 10°C after 48 h of laboratory storage was also 89 h, as the temperature shift started when discoloration of the TTI was already reached. Thus, the data infers that the discoloration of the TTIs occurred more quickly than expected, based on the expected shelf life, which was set by the initial charging time. During the charging process, the discoloration time of the TTIs is highly dependent on environmental influences, including temperature, relative humidity, and other factors, such as individual properties of the TTI batch and color batch, which was also shown in previous studies (Kreyenschmidt, Christiansen, et al., 2010; chapter 4). The deviations in this study showed that constant conditions are critical for ensuring reliable shelf life predictions by the app. Notably, the TTI prediction model, combined with the measured values, quite accurately predicted the residual shelf life. The shelf life calculated by the logistics model based on the app measurements was 88 h at 7°C, highly consistent with the predicted value of 89 h. For the 2°C scenario, the calculated shelf life was 156 h, considerably shorter than the predicted shelf life. The interplay of very low storage temperatures and high TTI charging times is challenging for the prediction. These weaknesses in the TTI prediction at low temperatures imply that the model must be further improved with more TTI kinetics data.

Table 5.2. Calculated remaining shelf lives of RTE salad (based on the growth of TVC on sliced carrots) based on real-time app measurements at different measurement points during the pilot study and during storage at different temperatures

Measurement point along the supply chain/ Calculation of the remaining shelf life	Time after production/ activation of the TTI [h]	Remaining shelf lives based on real-time app measurements [h] at different storage temperatures	
Transport and transshipment point 1 	No data available	**2.8°C (mean temperature during transport)**	
		No data available	
		2°C*	**7°C***
Transshipment point 2 	31	185	58
Retail store 	47	172	53

Storage	72		17	
				10°C*
Storage	120	97		
Calculated shelf life [h]		**217**	**89**	**89**

*storage temperatures after arrival at the laboratory. Samples were stored at 2°C and 7°C. After 48 h, some of the samples stored at 7°C were moved at 10°C to simulate a higher storage temperature at the hands of the consumer.

Regarding the shelf life of the RTE salad, the results of the pilot study confirmed sliced carrots as the shelf-life-limiting component, with the shortest microbial and sensory shelf lives at all temperatures. The shelf life was calculated to be 130 h at 7°C and, therefore, in good agreement with the laboratory investigations. Meanwhile, the shelf lives of mixed lettuce and corn at 7°C were 173 h and 189 h, respectively. The bacterial counts at 24 h were calculated to be 4.14 ± 0.36 $\log_{10}$ CFU/g and comparable to the previous results. This finding confirms the value of using predictive modeling. Also, Tsironi et al. (2017) and Kapetanakou et al. (2019) have shown that a shelf life prediction model for leafy RTE salad is a valuable tool along a supply chain with known temperature conditions. The quality prediction of RTE salad can be further improved by considering the prevalence and growth of pathogenic bacteria, such as *Salmonella*, *Listeria monocytogenes*, and Enterobacteriaceae, which are often found on fresh-cut products and constitute a health risk for end consumers (Arienzo et al., 2020; Calonico et al., 2019; Zeng et al., 2014). Next, the predicted TTI, measured TTI data by the app, and TVC growth on sliced carrots were compared (Figure 5.6). The comparison revealed that the TTI shelf life was shorter than the product shelf life, likely due to the unexpectedly faster discoloration of the TTIs, as previously described. The results for the storage at 2°C were comparable, with a product shelf life of 261 h. In this study, even if discrepancies occurred, and the TTIs could not accurately predict the shelf life of the product, there was generally good conformity between the OnVu™ TTIs and the product kinetics (Figure 5.7). Furthermore, this study provides an innovative approach by investigating and validating the use of the TTI color read-out and shelf life prediction by app for RTE salad, a specific and highly relevant food product, under laboratory and practical supply chain conditions. It offers a valuable, practical addition to previous studies, which were mainly focused on the technical part of the TTI read-out by app and the use as a temperature monitoring tool (Waldhans et al., 2023; Waldhans et al., 2024), by providing a proof of concept for the real-time shelf life prediction by app in practice. The consideration of a supply chain of a highly-perishable, plant-based product is also a novel approach in TTI research, as previously supply chains of meat products were regarded (chapter 4). If the product and TTI kinetics match, using predictive modeling by TTIs in the RTE fruit and vegetable sector and other supply chains is a valuable monitoring tool (Adiani et al., 2021; Park et al., 2013). The similar courses of the temperature-dependent curves suggest that the TTI shelf life can be better adapted to predict product shelf life by eliminating the systematic errors, i. e., insufficient charging of the TTIs due to different charging conditions in the pilot study. Further studies are needed to evaluate this hypothesis.

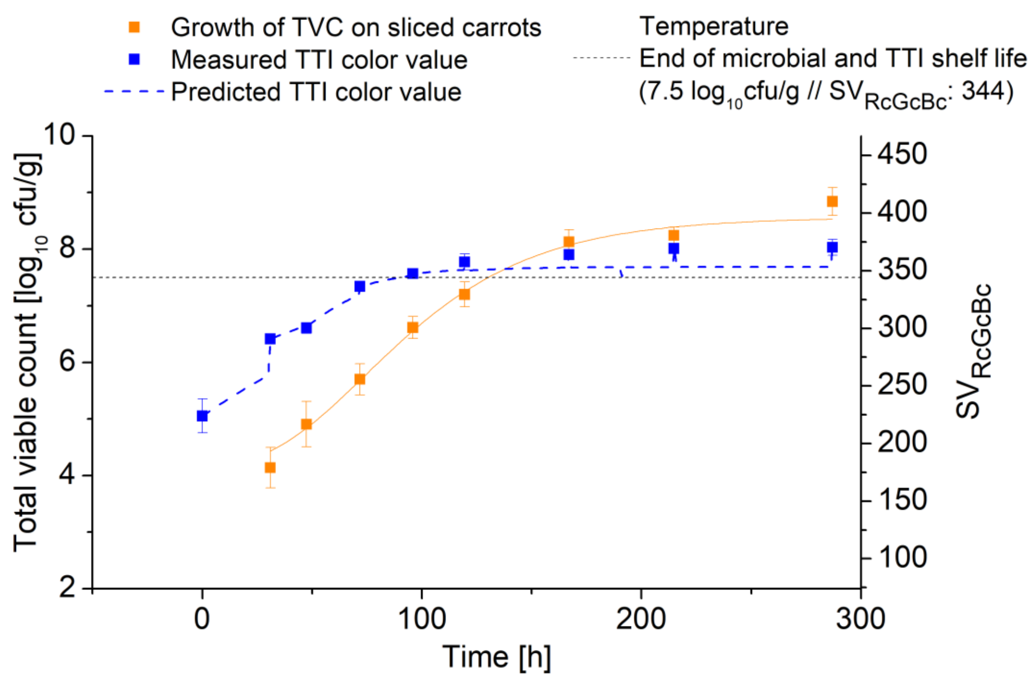

Figure 5.6. TTI color values both predicted and measured by the app in comparison to TVC growth on sliced carrots during transport along the supply chain and storage at 7°C (n=8 for each investigation point)

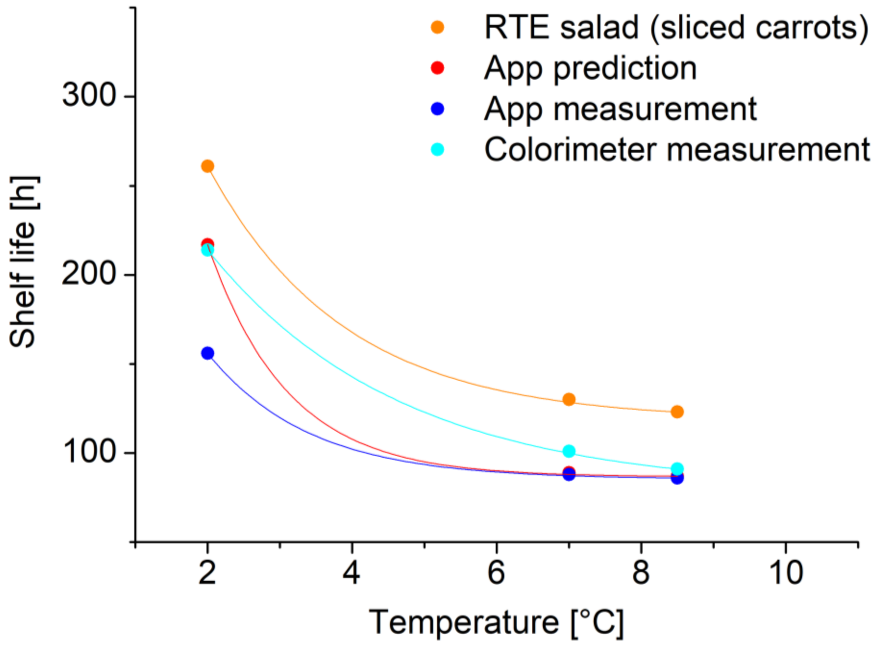

Figure 5.7. Microbial shelf lives of sliced carrots, TTI shelf lives both predicted and measured by the app and TTI shelf lives measured by the colorimeter at different storage temperatures in the pilot study

The results also show that measurements by the app were generally highly stable at the respective measurement points, exhibiting a comparable accuracy to colorimeter measurements. Models must be further improved to generate a reliable tool that stakeholders, as well as consumers, can use. TTIs must provide trustworthy and consistent information; otherwise, consumers will get confused and refuse to use TTI technologies (Pennanen et al., 2015; Verghese et al., 2015). Nevertheless, when TTI technologies are marketable, the application of TTIs and the high usability of a smartphone app can provide a valuable tool for consumers, especially with highly perishable and popular food products, such as RTE salad. In addition, to the technical evidence that the TTI system can be applied in practice, an increased knowledge about TTIs and their advantages is necessary on the consumer's side as one of the key drivers for novel packaging solutions (Sarma et al., 2023). For example, Fortin & Goodwin (2008) found that 75 % of Belgian consumers considered the use of Fresh-Check® indicators beneficial, and the majority would pay an additional amount for the application. Also, Zeinstra & van der Haar (2020) reported that Dutch consumers who received HelloFresh boxes equipped with Keep-it® indicators thought the indicators were valuable and increased the accuracy of quality and shelf life. Additionally, Tiekstra et al. (2021) showed that consumers were generally willing to pay more for an intelligent packaging system to a certain extent. Thus, the low single-unit costs of the OnVu™ TTIs are beneficial in terms of wider implementation in supply chains.

Also, more product information can be provided using the QR code. For example, Lau et al. (2022) revealed that consumers were positive about using a QR code to request an adapted shelf life and a possible discount on milk. However, Endara et al. (2023) reported that consumers needed an incentive to buy milk with a smart label instead of a static label, inferring that the benefit concerning sustainable effects was not widely broadly understood.

Consumers' trust in smart labels and their benefits need to be enhanced; in other words, more user experience is necessary (Barone & Aschemann-Witzel, 2022). In addition, a generally improved understanding of shelf life and temperature sensitivities is important. Abeliotis et al. (2014), Hall-Phillips & Shah (2017), and Yildrim et al. (2016) reported that the meaning and differences of "Best before" and "Use by" labels are confusing for many consumers in different countries and, as a result, influence their purchase and consumption decisions. Also, enhanced education concerning the enormous issue of food waste is necessary, as consumers who care less about food waste are also less willing to eat food after the labeled expiration date (Richter, 2017). Therefore, the app can also serve as an information tool and a value-added service.

5.5 Conclusion

The validation of an innovative TTI read-out system by an app for the shelf life prediction of an RTE salad was tested in this study under both laboratory and real supply chain conditions. The results showed a generally good correlation between the shelf life kinetics of the RTE salad's shelf-life-limiting component, the sliced carrots, and the discoloration kinetics of the OnVu™ TTIs. The study further uncovered some limitations due to varying charging conditions and inaccuracies in shelf life prediction under practical conditions. Thus, more practical investigations are needed to optimize shelf life modeling and use this approach to optimize supply chains and reduce food waste.

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6 General conclusion

The demand for sustainable and resource-efficient food supply chains has increased, especially regarding the food waste reduction. Concerning fresh produce, food waste is mainly caused by interruptions of adequate temperature conditions during transport and storage and expiry of the dated shelf life, which leads to discards and rejection at the consumer level. To improve supply chain monitoring, intelligent packaging is a promising technological approach. In the field of TTIs for temperature monitoring combined with shelf life prediction based on real temperature conditions, various developments were made in research and industry. However, although TTIs can serve as a helpful decision support tool for all stakeholders, the systems are still not widely used in practice. Barriers are varying requirements of different supply chains, a missing integration in operational traceability interfaces, and the elaborate read-out process by specific measurement devices. A digitalized read-out system is crucial to decrease these barriers; however, a simple analysis by smartphone, combined with shelf life prediction models for fresh produce is rarely described. Thus, the main objective of this thesis was the assessment of intelligent packaging systems for temperature monitoring and shelf life prediction of highly perishable products to improve resource efficiency along the supply chain of fresh produce and to serve as an opportunity to reduce avoidable food waste.

The first research question of this thesis addressed the analysis of a novel app-based system for the digital read-out of OnVu™ TTI discoloration based on color values. The color measurement using a smartphone app, which was programed to gather pixels of the discoloring part of the TTI and the surrounding white points on the label was tested in consecutive laboratory storage trials. The measurements were conducted after considering the defined environmental and technical parameters influencing the color measurement, that is, light conditions, measurement distance, and smartphone type as well as the initial charging time of the label and storage temperature. Results revealed that the considered parameters had a moderate to high influence on gathered color values using the app. Based on these findings, a measurement correction through white balancing was applied, which clearly reduced data variations and enabled stable color measurements by the app even under varying conditions.

Based on these first results, the app was technically adjusted, and a QR code scanner was integrated. Furthermore, the well-established OnVu™ label has been extended with a QR code. TTI discoloration kinetics were then analyzed using the corrected color measurements by app during storage trials at different temperature conditions with varying charging times. The measurements were compared to conventional measurements by colorimeter as a reference. The investigated discoloration kinetics at 2°C–15°C enabled the development of an app-based TTI shelf life model. The calculated activation energies (25.69–26.66 kcal/mol) demonstrated that TTI kinetics can reflect spoilage kinetics of several food products. Calculated discoloration kinetics using the app and colorimeter were comparable, revealing that the app could serve as a reliable measurement tool for TTIs. The sensitivity limitations of app measurements at high charging times in combination with low temperatures in the lighter color range were also revealed. Integrating a QR code is valuable to provide specific supply chain information. A digital basis with a smartphone application for measurements, data acquisition, and processing as well as information availability serves many possibilities for a more efficient food supply chain management. The continuous information flow concerning shelf life status and temperature between stakeholders allows reduction of food waste and improvement of logistics management. The results served as a basis for further investigations in model application and validation.

The second research question aimed to evaluate the current situation on temperature control in the fresh produce industry and retail, the use of temperature monitoring systems, and ways of data management in supply chains of food products. The survey provided information regarding applied temperature monitoring devices, data storage, and exchange systems and identified challenges and weak points along the cold chains. This survey also focused on the current use of intelligent packaging systems and the situation concerning digital systems for data recording and exchange. An online survey of 45 stakeholders was conducted, including food production and processing, transport and logistics, as well as wholesale and retail of perishable food.

Results of the survey revealed that the control of ambient temperature conditions is mainly conducted, as well as the control of other static conditions such as a visual inspection and the control of the date label. Mainly classical temperature monitoring devices – non-contact and contact thermometers and electronic data loggers – are used from participating stakeholders for obligatory temperature controls. TTIs as well as RFID and other smart labels play a minor role in their use. Furthermore, results revealed that stakeholders mainly apply paper-based documentation, whereas digital documentation advantages are known, such as time saving and simplification of data storage, sharing, and traceability. Data sharing between stakeholders mainly occurs by written documentation and on request or if necessary. The status quo has not substantially changed compared to the last decades, and stakeholders are still only using the well-established temperature monitoring devices in combination with conventional documentation procedures. However, general awareness for the benefits provided by digitalized monitoring systems was also revealed by the survey results. This can serve as an approach in implementing app-based TTI systems based on stakeholder needs.

The third research question analyzes whether the app-based TTI system can serve as a reliable temperature monitoring tool in different supply chains. Therefore, the app-based TTI system was tested in three different practical studies, considering a B2B supply chain for fish, a B2C supply chain for raw pork sausage, and a B2C e-commerce supply chain for mixed goods. TTIs were attached at defined positions to the respective packaging units – polystyrene boxes, single packaging units, and insulated cardboard boxes, respectively – and transported along the individual supply chain. In all studies, the packaging units were afterward stored at the laboratory at defined temperature settings. During transport and storage, TTIs monitored the real temperature conditions, and in parallel, app and colorimeter measurements were conducted.

Results for temperature monitoring using app-based TTI measurements in the B2B supply chain revealed that temperature conditions within the polystyrene box at different positions can generally be reflected. An unexpected temporary increase in ambient temperature during box storage could clearly be displayed through app measurements, indicating a generally adequate sensitivity to weak points. Extremely varying light conditions during measurements led to inaccuracies in app color values, resulting in high standard deviations. Colorimeter measurements could represent temperature differences at positions more reliable than app measurements. Temperatures in the B2B supply chain for raw pork sausage demonstrated minor variations from the production to arrival at the factory sale. In this supply chain, app measurements of the TTI showed standard deviations, which were comparable to the reference measurements by colorimeter. Moreover, analyses showed that high temperature differences during storage at the laboratory, with several degrees difference, could be well reflected by app, whereas slight differences could not be clearly differentiated. Regarding temperature monitoring in the e-commerce supply chain, TTIs on inlays within the mixed boxes could well reflect varying mean temperatures in different boxes during transport in the chain. This could be also seen during storage at simulated summer and winter scenarios with several variations of the temperature from 20°C to 32°C and -2°C to 9°C, respectively. In general, enhancement in the accuracy of the app measurements, which is mainly affected by environmental conditions in practice, can improve the suitability as a reliable temperature monitoring tool, which operates as precise as a well-established colorimeter.

The last research question aimed at the investigation of the app-based TTI system as a shelf life prediction tool in two B2C supply chains for the highly perishable products raw pork sausage and RTE salad. Shelf life models of the product were first developed based on the individual microbial spoilage kinetics examined in laboratory storage trials at different constant and dynamic temperature conditions. Combining the product shelf life models with the TTI shelf life models, the application of the app-based system was tested under real supply chain conditions. The selected products were each equipped with TTIs immediately after packaging and afterward transported along the chain including individual steps of the chain. Post-transport, storage at different temperature conditions was simulated at the laboratory. TTIs were measured using the app and colorimeter at selected time points, and the real-time remaining shelf life was calculated. Results of the study with raw pork sausage revealed that spoilage kinetics of the product and TTI discoloration kinetics generally showed high comparability. This is the main prerequisite for the application of the TTI as a shelf life indicator for the selected product. In the study on the RTE salad, the shelf life model was built based on determining the limiting shelf life of sliced carrots, which also indicated a high accordance with the TTI shelf life.

In both studies, predicted and measured TTI color values by app were in high accordance. The shelf life prediction of raw pork sausage using the app showed differences in the hourly range. For RTE salad, shelf life prediction using the app under laboratory conditions showed highly appropriate results. In the practical study with RTE salad, variances were partly high with shorter shelf lives for the product predicted using the app than the actual product shelf life. These two studies could basically serve as a proof of concept for the general possibility to use the app-based TTI system in perishable food supply chains when product kinetics agree with TTI kinetics. App-based systems should be further improved regarding technical adjustments and adaptation of the appropriate charging time. These can help to increase its accuracy, especially when measurements are influenced by external factors.

The results of all conducted studies can conclude that intelligent packaging systems, i.e., TTIs, applied with the use of the novel app-based read-out system, can monitor temperature and predict the shelf life of fresh produce. This allows the application of an LSFO approach in warehousing instead of an FEFO principle, which can reduce food waste along the chain. Thus, intelligent packaging with an app-based read-out can generally operate as a promising tool to enhance the resource efficiency by optimized supply chain management. The resources used along the supply chain, that is energy, water, livestock, and other valuable environmental resources, which have been misspent in case of food waste, can be saved. The application of TTI systems in practice is still challenging, even if basic conditions for a well-functioning system are given. Further studies must be carried out, especially to improve the measurement sensitivity and model accuracy. In this context, shelf life data of companies and artificial intelligence (AI) approaches can help significantly improve future shelf life predictions. The continuous, real-time monitoring of product shelf life and influencing parameters combined with AI-driven systems, such as machine learning algorithms, serve as a promising approach. Scientific literature shows that studies have already been carried out on this subject and it could be expected that the increasing digitalization of shelf life prediction in food systems will increase even further in the upcoming years.

The app-based color read-out and shelf life prediction TTI system developed and assessed in this thesis can provide as a groundwork to adapt the read-out procedure and shelf life models to other TTI systems based on a color change. Future studies should evaluate one approach that may be the combination of intelligent packaging systems with active packaging solutions or pathogen indicators to further increase the resource efficiency of a food product. Synergies can be then used by considering the individual properties of these systems. The serial individual product identification by the TTI using the QR code also offers advantages in this respect. Then, the measured data by the packaging systems can be assigned on an individual product level. The application of the intelligent labels on a single product level must be further considered regarding the investments that a company has to make for the accompanying technique for the implementation of the described system. Depending on an individual cost-benefit-analysis, the app-based TTI system is especially valuable for perishable products affected by high food waste amounts, as the conducted studies showed.

Concerning the intelligent label, recyclability and waste management should also be considered to realize an overall sustainable process. In this context, the additional packaging waste should also be carefully considered in future, as TTI application and food waste reduction should not lead to contrasting effects. However, resource-intense packaging can also be more sustainable if it saves food waste in the overall process.

As a concluding remark, the barriers of data sharing must be removed for a successful practical application of the app-based TTI system, as the trust along the supply chain is still of great concern. Further information and training for stakeholders on the use of intelligent packaging systems and their advantages in resource saving should be provided. For consumers, additional information about shelf lives and temperature sensitivities of food products can be integrated in the app. The developed app-based system provides a good basis to customize the application to specific user profiles. Thus, user-specific information can be shared, e.g., with the aid of easily comprehensible dashboards. This can increase the overall understanding of food products, packaging, and the connection with the use of valuable resources.

Appendix

A.1 Appendix for chapter 2

Table A.1. Mean raw SV_{RbGbBb} values for TTIs measured under the influence of different parameters, activated with 1800 ms and stored at 7°C

		0 h		168 h		360 h	
		Light conditions					
Smartphone	**Distance**	**Daylight**	**Ambient**	**Daylight**	**Ambient**	**Daylight**	**Ambient**
Nokia 7.2	10 cm	145.58 ±4.92	104.89 ±4.76	256.30 ±7.36	205.81 ±7.25	279.02 ±3.35	240.41 ±13.70
	2x zoom	165.59 ±4.51	120.20 ±3.35	288.71 ±3.66	257.65 ±9.16	308.48 ±2.92	282.80 ±6.47
XIAOMI Mi Note 10 Lite	10 cm	-	122.47 ±3.21	-	243.19 ±6.78	-	271.11 ±7.03
	2x zoom	179.87 ±2.32	145.10 ±5.66	281.94 ±4.52	272.73 ±3.70	300.00 ±2.51	302.23 ±3.85

A.2 Appendix for chapter 5

Table A.2.1. Scheme for the 5-point-scale sensory evaluation of RTE salad, separated by the different components and their characteristics for each point and attribute

Attribute		Mixed lettuce	Corn	Sliced carrots
Color	5	fresh, intact leaves	bright yellow, glossy, fresh	strong orange, juicy
	4	fresh, light condensation formation, light pressure spots	yellow, glossy, fresh, light browning of the cut surface	strong orange, juicy with dry spots
	3	pressure spots with discoloration, volume reduction	damp to wet, yellow, browning of the cut surface	damp
	2	little fresh appearance, pressure spots	yellow to grey, faded, damp to wet	damp to wet, deeper orange
	1	dark, not fresh, wet, rotten	pale, clear mucus	wet, deeper orange
Texture	5	crisp, firm	artisan, crisp	crisp, firm
	4	mostly crisp, stable	elastic	mostly crisp, soft in bright spots
	3	partly not stable, soft	liquid discharge at pressure	partly crisp
	2	soft to brittle, mostly not stable	wet, hollow	soft, brittle
	1	muddy, wet	pulls mucous threads	soft, no breakage, not stable
Odor	5	fresh, cabbage-like	artisan, sweet, fresh, aromatic	intense, artisan, sweet, fresh
	4	fresh, cabbage-like, sweet, fruity	artisan, sweet, starch-like	artisan, sweet, fresh
	3	sweet, hay-like	slightly acidic, less artisan	flattened odor, less sweet
	2	hay-like, slightly acidic	acidic, hardly artisan	acidic, musty
	1	unpleasant, acidic	unpleasant, acidic, bitter, stinging	sour, stinging, alcoholic

Table A.2.2. Parameters obtained from the Gompertz model describing the microbial growth of TVC on sliced carrots and from the linear model describing sensory changes of sliced carrots at different isothermal storage temperatures

Temperature [°C]	Microbial Growth of TVC			Sensory evaluation	
	xc	***k***	R^2	***Slope***	R^2
2	114.18534	0.01004	0.9526	-0.00419	0.99828
4	86.35251	0.01744	0.99837	-0.00685	0.9812
7	58.00096	0.02185	0.99855	-0.00953	0.99843
10	39.17773	0.04322	0.99856	-0.01574	1
15	45.23391	0.07018	0.98144	-0.02421	0.98947

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2025

Waldhans, C., Albrecht, A., Ibald, R., Wollenweber, D., Kreyenschmidt, J. (2025). Implementation of a time-temperature-indicator as a shelf life predictive tool for a ready-to-eat salad. *Applied Food Research 5*, Issue 1, 2025, 100640. https://doi.org/10.1016/j.afres.2024.100640

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