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Scientific, Smart & Safe: Sensor Technology as a Marketing Tool to Increase Restaurant Visits During COVID-19

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Summary

Inspired by the possibilities of novel IoT sensor technology, this master's thesis tests a new way to encourage customer visits to restaurants at the time of the COVID-19 pandemic. Inspired by recent advances in sensor technology and drawing from the servicescape and risk perception literature, we hypothesize that information about the regulation of environmental dimensions through IoT ambient and occupancy sensors increases customers' willingness to visit restaurants by increasing customers' perceived safety. We also argue that the effect of the information about the regulation of environmental dimensions through IoT sensors on customers' perceived safety is moderated by the customers' perceived threat of COVID-19. Data from an online experiment in Qualtrics with 392 adult restaurant-goers were analyzed in SPSS through mixed-model ANOVA, linear regressions, mediation with PROCESS, and GLM analysis. We found strong evidence that information about IoT sensors that regulate the restaurant's environmental dimensions indirectly increases customers' willingness to visit the restaurant. We also found strong statistical evidence about the mediating role of perceived safety and the moderating role of customers' perceived threat of COVID-19. We give theoretical and strategical recommendations for the implementation and value communication of IoT sensors as a marketing tool for reassuring customer safety during the COVID-19 pandemic.

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1 Introduction

1.1 Background

The unexpected outbreak of the COVID-19 global pandemic has changed the business environment worldwide. Companies face challenges related to consumer demand, health and safety, the supply chain, the workforce, cash flows, sales, and marketing (Donthu & Gustafsson, 2020). Faced with revenue loss and for some, possible risk of bankruptcy, companies have to rethink their business models and come up with new ways to satisfy customers' needs and wants while complying with COVID-19 government regulations (Seetharaman, 2020). Industries providing in-person services are the most negatively affected by the COVID-19 pandemic.

Restaurants, in particular, have suffered from governmental restrictions aimed at containing the spread of COVID-19, such as lockdowns and social distancing (Apkan et al., 2020). The new status quo has changed the way restaurants conduct their businesses and the way customers prioritize their choices, preferring takeaways and delivery food more often than in the past (Gomes de Freitas & Stedefeldt, 2020). As a consequence, 27.5% of restaurateurs will close some locations and 16.1% of them will permanently close their business (Gomes de Freitas & Stedefeldt, 2020). The most financially affected are smaller restaurants with less cash flow, leverage, and ROA (Song et al., 2021). At one of the pandemic peaks in April 2020, the bar and restaurant industry saw a 58% drop in revenue (Gomes de Freitas & Stedefeldt, 2020). In the United States of America alone, millions of restaurant employees lost their jobs (Nhamo et al., 2020).

Restaurants must now comply with new health and safety standards aimed at maintaining an optimal distance between customers. But, even if a restaurant complies with social distancing regulations, many customers are still reluctant to engage with the service, fearing that these measures may not be enough to guarantee their safety and may expose them to potential health hazards. Even after regulations relax, reopening restaurants might not bring customers back because a majority might not be willing to dine in at a restaurant immediately (Gursoy & Chi, 2020). Thus, restaurateurs need a new approach to market their services. A recent study on customer’s perceived risk in restaurants during the COVID-19 pandemic found that the perception of safety predicts the intention to visit a restaurant (Hakim et al, 2021). However, the perception of safety has only been studied regarding the trust in the restaurant's brand, and not extended to the more general concept of a servicescape. Despite the urgent attention academic research has addressed to COVID-19, research is inconclusive about what can make customers return to dining out (Gursoy & Chi, 2020). Given the high operational costs in restaurants, figuring out what will make customers return is essential to the continued operation and survival of the industry. A special focus on the deployment of emerging technology can guarantee customer safety, which may help bring back customers and rejuvenate the restaurant industry (Verma & Gustafsson, 2020).

1.2 Definitions

Sensors are technological devices that are distributed in an environment to detect and collect data from that surrounding environment (Tenney & Sandell, 1981). The kind of information that sensors detect will depend on the type of sensor used. In this study, we focus on four types of sensors: humidity, temperature, CO_2, and occupancy. Thus, a humidity sensor detects the level of humidity in the surrounding environment, a temperature sensor detects the surrounding temperature of a space or surface, a CO_2 sensor detects the density of carbon dioxide in the surrounding air, and an occupancy sensor detects the presence of an object or person in its surrounding proximity. Data gathered from sensors needs the application of analytics and user-friendly interfaces that visualize the data and propose actionable recommendations. Thus, sensor-based solutions are now deployed, which include analytical software and visualization tools, so that the user can receive actionable recommendations based on the data gathered by the sensors.

The Internet of Things (IoT) has become a buzzword in the last decade due to its expansion and adoption. The definition of IoT has thus evolved with the technology, and there is currently no academic consensus on a clear understanding of its meaning (Wortmann & Flüchter, 2015). In the context of this thesis, we refer to IoT to describe the network technology that the sensors in our study use to transmit their data, which is a wireless internet network. Thus, the term *IoT sensor* is used throughout this thesis to describe a detecting device that transmits the data it detects over a boundless network on the internet, and whose data can further be visualized and analyzed through a sensor-based software solution that gives actionable recommendations based on the data.

1.3 Focus

In the context of COVID-19, we focus on IoT wireless sensors capable of measuring humidity, temperature, CO2, and occupancy. Humidity, temperature, and CO2 sensors can help reinforce customers' safety, indicating the risk of virus spread in the air. Various studies have shown that the majority of transmission cases happen indoors (Public Health England Transmission Group, 2020) at high levels of humidity and temperature (Magd et al, 2020; Mecenas et al, 2020; Cao et al, 2021). Further, one study conducted in Spain showed that optimizing indoor temperature by an increase of 1°C reduced the incidence rate of new cases by 7.5% on the same day (Tobìas and Molina, 2020). This is consistent with previous research on influenza virus transmission, which has identified absolute humidity and temperature as climatic predictors of influenza epidemics (Lowen & Steel, 2014; Lowen et al, 2007). CO2 concentration in the air is another predictor of COVID-19 virus transmission. High levels of CO2 in the air can increase the fatality rates from COVID-19 because of the adverse effect on the respiratory system (Cao et al, 2021). IoT sensors that monitor for high CO2 levels signal restaurateurs when it is time to ventilate and can signal faults within the restaurant's ventilation systems. Improving ventilation is essential to reduce the threat of COVID-19 spread, as the risk of transmission may increase if no window or door is open (Morawska et al, 2020; PHE Transmission Group, 2020).

On top of improving ventilation, an increase in the distance between tables and customers is also recommended (Lu et al., 2020). As social distancing is now a fundamental requirement for businesses to reopen, sensors that give space occupancy insights can ensure that optimal distance is respected. By placing non-intrusive occupancy sensors underneath chairs and tables, restaurateurs can get an overview of their spatial layout and how their space is being used in real-time. The sensors detect the presence of people near the area in which they are placed, creating an occupancy heatmap. This technology thus not only gives insight into occupancy density but can also help secure social distancing measures are implemented. With the data insights gained from IoT occupancy sensors, restaurateurs can then design the best possible space to comply with social distancing regulations and be alerted through IoT-enabled notifications if there are any problems.

1.4 Thesis objective and implications

Inspired by the possibilities of IoT sensor technology in mitigating COVID-19 related risks, we aim to answer the following research question: *"How does informing customers about the regulation of a restaurant's environmental dimensions through IoT sensors affect customers' intention to visit the restaurant?"* We argue that the effect is achieved by influencing the customer's internal safety response to the environment through anxiety reduction, where the safety response is moderated by the customer's perceived threat of COVID-19.

Given the recent need for more research-based solutions on how restaurants can mitigate the financial risks brought by the COVID-19 pandemic, this study can provide insight into how restaurants can use advancements in IoT sensor technology to reassure customers on the safety of the restaurant's indoor environment. Further, the findings and implications of this research can lay the foundation for studying the effect of IoT or similar technology in other service settings and the context of other future epidemics or pandemics that require similar ambient conditions and space occupancy regulations, predicted to become more frequent and fatal (Dodds, 2019; Chin et al, 2020).

1.5 Layout

This thesis is organized as follows: First, we introduce the study's central conceptual framework, Bitner's framework on servicescapes (1992). Second, we put forth our research framework based on Bitner's (1992) findings. Our research framework describes the relationship between our independent variable, *information about the regulation of restaurant environmental dimensions through IoT sensors*, and our dependent variable, *willingness to visit the restaurant*. Our research framework also serves as the foundation for our hypotheses. Third, we lay out our methodology regarding the type of study we conducted, as well as data collection and analysis methods. Finally, the results of the study are presented and discussed, as well as their theoretical and managerial implications.

2 Conceptual Framework

A servicescape refers to the man-made built environment that surrounds a service (Bitner, 1992). Since by definition a servicescape is “man-made”, restaurant managers or owners can build or shape the restaurant’s environment to impact customer responses and behavior. Bitner’s (1992) conceptual framework on servicescapes describes the impact of physical surroundings on both customers and employees (Figure 2.1). Both groups, also referred to as users of the environment, experience their environment holistically but as a composite of three dimensions. Bitner argues that this perceived servicescape, i.e., the overall holistic environment in which a service takes place, influences a customer’s and employee’s behavior through impacting their internal responses (cognitive, emotional, physiological). This effect is moderated by personal and situational factors. Figure 2.1 visually demonstrates this conceptual model.

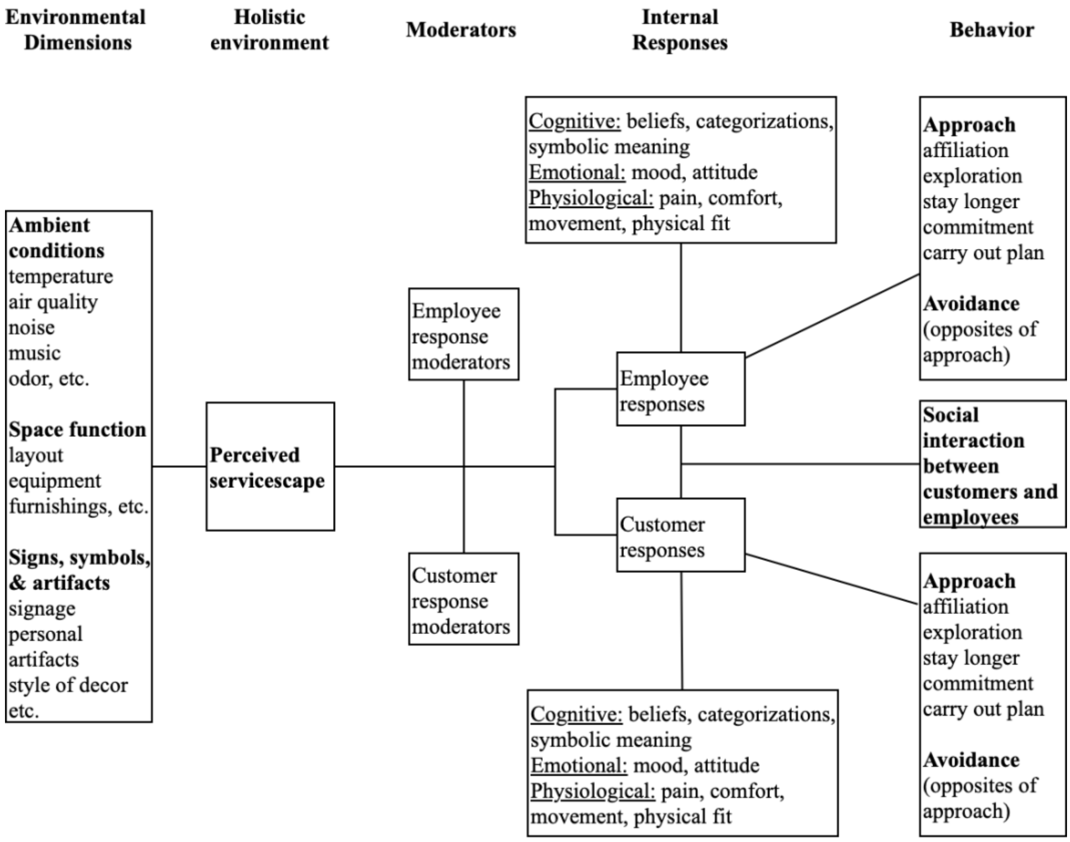

Figure 2.1. Framework for Understanding Environment-User Relationships in Service Organizations. Source: Bitner (1992).

2.1 Servicescape & Behavior

The servicescape model predicts that if a customer or employee responds to the environmental dimensions of the servicescape positively, then the users will exhibit positive behaviors, like attraction, further expenditures, or repeating the service experience (Donovan & Rossiter, 1982; Milliman, 1982, 1986). These employee and customer responses will also define the social behavior between customers and employees, defined as their social interactions. The servicescape theory predicts that restaurants can achieve their marketing goals and desired approach behaviors through careful and creative design and management of the servicescape. Customers and employees engage with the servicescape to achieve a goal, and the servicescape could either help or hinder the completion of that goal. For example, if the music in a restaurant is too loud so that the employee is having a difficult time taking a customer's order, the design servicescape is getting in the way of the employee's goal to serve the customer and the customer's goal to have an easy and pleasant dining experience, and thus might subsequently influence behavior.

Each element of the environmental conditions can play a role in customer and employee perception, mood, attitude, or comfort and thus influence customer and employee behavior, as well as their social interactions. These behaviors can be positive, i.e., approach behaviors, like the desire to stay, explore, work, and affiliate in the servicescape, or negative, i.e., avoidance behaviors that reflect the opposite (Mehrabian & Russell, 1974; Bitner, 1992). The servicescape can also act as a differentiator through the restaurant's signs and symbols and can help with the overall positioning of a restaurant against competitors. How the elements of the servicescape will influence the customers' and employees' behaviors will depend on the users' internal responses to the environment and will be moderated by personal and situational factors, which are discussed in the following sections.

2.2 User Internal Responses and Moderation

It is widely accepted that humans are affected by the environment they interact with (Darley & Gilbert, 1985; Holahan, 1982; Russell & Ward, 1982; Stokols & Altman, 1987). The servicescape framework argues that the holistic environment particularly influences cognitive, emotional, and physiological customer and employee internal responses. These cognitive (beliefs, categorizations), emotional (pleasure, arousal), and physiological (pain, movement, comfort) internal responses are moderated by personal and situational factors. Their degree of influence on the customer's and employee's behavior will thus depend upon the user's personality traits, like arousal-seeking tendencies and ability to screen environmental stimuli, and situational factors like expectations, mood, plans, and purposes for being in the servicescape (Bitner, 1992).

Cognitive internal responses are positive and negative beliefs, attributions, and categorizations. The servicescape theory predicts that a user's positive perception of the restaurant servicescape will lead to positive cognitive internal responses (Kim & Moon, 2009). The servicescape itself can be regarded as a form of nonverbal communication from the restaurant to the user, and the user can extract meaning from the surrounding environment (Ruesch & Kees, 1956). These perceptions of environmental cues also influence how customers perceive and categorize the restaurant, which can be a source of differentiation and competitive advantage (Ward et al., 1988). The influence of the servicescape on beliefs, attributions, and categorization is stronger for customers who have little to no previous experience with the restaurant (Zeithaml, 1988). In a restaurant, intrinsic attributes commonly associated with tangible products, e.g., taste, smell, or plate presentation are not available for a first-time customer to receive cues from until an order is placed and experience with the restaurant is gained (Zeithaml, 1988). Thus, customers with little to no experience depend on extrinsic attributes of the service experience to form their initial judgment and categorization more than intrinsic attributes, alleviating the importance of the servicescape for first-time users.

A restaurant's servicescape also influences a user's emotional responses, like his/her mood and attitude, which in turn influence the user's behavior within two dimensions, pleasure and arousal (Mehrabian & Russell, 1974; Russell & Lanius, 1984; Russell & Pratt, 1980; Russell & Snodgrass, 1988). The perception of greater personal control within the environment, the presence of natural elements, and the absence of environmental "annoyances" increase the user's pleasure with the servicescape (Hui & Bateson, 1991; Nasar, 1987). On the other hand, the level of complexity (visual richness, decor) in the servicescape increases emotional arousal

(Nasar, 1987). Pleasure and arousal elicit emotions that influence the user's perception of the servicescape and associated feelings with the restaurant, its people, and its service.

Last, physiological responses, such as pain, comfort, movement, or physical fit also influence user perceptions of the restaurant. For an interpersonal service, like a restaurant, an effective design of the servicescape influences user responses to the environment and also creates the foundation for the service encounter between the customer and the employee (Bitner, 1992). Thus, the restaurant identifies desired goals and behaviors for its customers and their interactions with the employees. The restaurant can then design its servicescape to reflect those desired behaviors and thus positively influence internal responses.

2.3 Dimensions of Servicescape

The three dimensions which make up a restaurant's holistic environment are (1) Ambient conditions, (2) Spatial layout and functionality, and (3) Signs, symbols, and artifacts. These dimensions interact with each other; therefore, their effects can be seen in combination with other dimensions as well as individually. Conditions that make up a restaurant's ambient conditions are temperature, air quality, noise, music, odor, etc. (Bitner, 1992). These conditions are specifically noticeable when they are alleviated or extreme, the user spends considerable time in the servicescape, or when they conflict with expectations. For example, the user will be most affected by ambient conditions if a restaurant is very cold or hot, the customer dines in instead of ordering take-aways, or if the restaurant is fine-dining and plays rock metal music, contradicting expectations. These dimensions can also be barely noticeable by the senses and still have a profound effect on users. The quality of air, ambient gases, and chemicals, or infrasound have been shown to impact the user's experience, especially if users are exposed to them for a long time (Russell & Snodgrass, 1987).

Spatial layout and functionality refer to the degree to which the characteristics of equipment or furniture allow users to accomplish their goals. These are especially important in self-service settings for the customer or when the employee is under time pressure. Last, signs, symbols, and artifacts communicate a restaurant's personality and service concept and help to form first impressions. They can also play a differentiating role in highly competitive industries like the restaurant business, as customers are looking for cues to differentiate restaurants. For example, the choice of white tablecloths, silverware, minimalistic design, and dim lighting communicate high prices and high-end services. Whereas through plastic trays, bright lights, and popping colors, customers infer they are in a lower-priced fast-food environment (Bitner, 1992).

3 Research Framework

The relationship between environmental dimensions, customer internal responses, and approach behaviors has been laid out by Bitner (1992), as described in the previous section. Siguaw et al (2019) also incorporated a safety construct into Bitner's framework (1992) as part of the environmental dimension. The results were consistent with previous research, showing that ambient conditions, physical spaces, and social interactions, as well as safety, are the primary concerns for consumers. These implications of the servicescape theory can help create a conceptual framework to study the effect that information about IoT sensors can have on customers visiting restaurants during COVID-19. Our framework describing the latent variables of this study is illustrated in Figure 3.1 and is derived from Bitner's (1992). To align with this thesis' objective, we leave out the employees' responses and the social interaction between employees and customers and will only focus on the customer's experience with the servicescape.

Because the relationships between our latent variables have not been studied before in our established setting, it is important to establish these relationships before testing for mediation. According to Baron & Kenny (1986), to account for the direct and indirect effects of the regulation of ambient conditions through IoT sensors on customers' willingness to visit the restaurant, we must show that:

i. Information about the regulation of ambient conditions with IoT sensors has a positive effect on customer's willingness to visit the restaurant (*H1*)
ii. Information about the regulation of ambient conditions with IoT sensors has a positive effect on customer's perceived safety (*H2*)

iii. Customer's perceived safety has a positive effect on customer's willingness to visit the restaurant (*H3*).

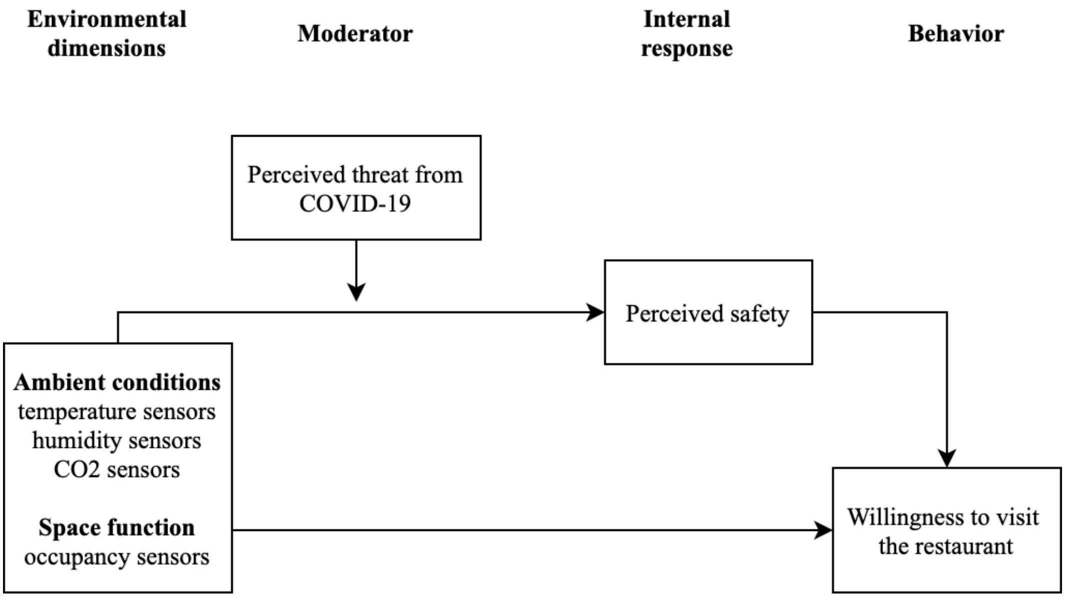

Figure 3.1. The framework of the relationships between latent variables, based on Bitner (1992).

Thus, if these relationships are established, we propose that customer perceived safety mediates the relationship between the regulation of ambient conditions through IoT sensors and willingness to visit the restaurant (*H4)*. We further propose that the relationship between the regulation of environmental dimensions through IoT sensors and safety is moderated by the customer's perceived threat from COVID-19 (*H5)*. Thus, customers that perceive the threat from COVID-19 differently will exhibit different perceived safety responses to the regulation of ambient conditions with IoT sensors.

3.1 IoT Sensors & Willingness to Visit the Restaurant

It is a marketing truism that the physical setting in which a service takes place influences customer behavior (Kotler, 1974; Parasuraman et al., 1985; Bitner, 1992). Ambient conditions, background elements that influence the subconscious, like heating, ventilation, and air conditioning (Wineman, 1982), make for an important part of the restaurant service experience. Although customers do not consciously perceive these ambient conditions, they can identify when an element is missing or is at an extreme. Thus, when a customer's senses are made aware of certain ambient conditions, it increases the probability of positive behaviors when the ambient factor enhances the service experience. (Baker, 1986).

During COVID-19, regulation of environmental dimensions with IoT sensors minimizes infection risk. IoT temperature, humidity, and CO2 sensors measure air quality ambient conditions that influence the airpath of COVID-19 transmission. Air quality control, therefore, makes most customers feel more comfortable in a restaurant during COVID-19, leading to a better service experience (Carbon Lighthouse, 2020). An improved service experience has been proven to encourage positive behaviors, like restaurant visits (Andaleeb & Conway, 2006). Thus, the presence of IoT sensors that measure COVID-19 related ambient conditions, like temperature, humidity, and CO2 enhance the restaurant's service experience, which in turn might encourage restaurant visits.

Another important element of a restaurant's service experience is the functional design of the space. The space arrangement (layout) and comfort of the space can greatly influence customer behavior due to its more perceptual nature. A positively perceived space can elicit positive emotional responses, like a positive mood and attitude, which increase the probability of approach behaviors, like staying in, exploring, or visiting the restaurant (Baker, 1986). Further, organizational and marketing objectives could also potentially be targeted through effective occupancy design. Non-intrusive occupancy sensors stuck in tables and chairs give restaurateurs an overview of space utilization and encourage spatial design to comply with COVID-19 regulations. Social distancing can help reduce the spread of COVID-19 infection and is a requirement in most countries for restaurant operations (Udgata & Suryadevara, 2020). A restaurant's occupancy that scientifically implements social distancing not only influences pandemic-compliant behavior but can also create an image of a restaurant as technologically advanced and compliant with regulations, a positive association that has been demonstrated to directly influence approach behavior like restaurant visits (Upah & Fulton, 1985; Bitner, 1992). Thus, since ambient conditions and occupancy have been demonstrated to affect approach behaviors, like restaurant visits, we predict that the regulation of these environmental dimensions through IoT sensors will similarly influence customers' willingness to visit the restaurant.

H1a. Information about IoT sensors that measure ambient conditions in restaurants has a positive effect on customer willingness to visit the restaurant.

H1b. Information about IoT sensors that measure occupancy in restaurants has a positive effect on customer willingness to visit the restaurant.

3.2 IoT Sensors & Customer Perceived Safety

Most literature on IoT sensors is concerned with the technology's effects in an environmental, health, safety, manufacturing, industrial, or high-risk setting. In these settings, IoT sensor technology has reduced human errors and material casualties in disasters, thus increasing overall workplace safety (Thibaud et al., 2018; Kantarci & Mouftah, 2014). Sensors monitor the environment and are installed in assets like voltage fuses, substations, or power grids, and even the human body. Coupled with automation and machine learning technology, they collect data and alert maintenance staff of possible overheating and fire risks, leading to fewer accidents and better environmental performance for the energy systems they monitor (Khatua et al., 2020). Temperature sensors can also monitor cold storage equipment, like fridges or freezers, and ensure food is being kept fresh, thus reducing the risks of food-related illnesses. Thus, environmental dimensions that can be detected and monitored through sensor technology can lead to changes in behavior and overall better optimization of risky processes.

Echoing these advancements on the contribution of IoT sensor technology to safety, we argue that IoT sensors can be an adequate technological response to address decreased customer perceived safety in restaurants due to the risk of infection by COVID-19. In this study, we define customer perceived safety as the customer's perceived absence of unwanted risk or harm (Hollnagel, 2014). Thus, the factors that positively influence individual perceived safety are factors that add to negative perceptions of risk or harm: attitude (as a function of beliefs and values), risk sensitivity, and the context of the specific fear that brings about an absence of safety all influence risk perception (Sjöberg, 2002), and subsequently, safety perceptions.

Gomes de Freitas and Stedefeldt (2020) argue that restaurants must adopt safe practices, as customers will only dine-in in places they perceive as safe. Further, restaurateurs should make data-based decisions regarding the infrastructure of their service to increase customer safety (Gomes de Freitas & Stedefeldt, 2020), thus transforming their servicescape to accommodate recent changes in customer behavior. Preliminary findings suggest that around one-third of restaurant customers are willing to pay more for increased safety precautions (Gursoy & Chi, 2020). Thus, restaurants that can effectively communicate the adoption of these new technologies might provide a new added value, increasing the customers' perceived safety in an indoor environment.

Airborne transmission of COVID-19 in indoor environments can be minimized by the use of engineering controls that sensors measuring humidity enable, in collaboration with other measures such as social distancing, which are enabled by occupancy sensors (Morawska et al., 2020). Thus, the deployment of IoT sensor technology that measures areas of concern in COVID-19 transmission can minimize infection risk by regulating a restaurant's environmental dimensions. Consequently, ambient conditions and occupancy regulations in a restaurant can make customers feel safer by communicating the implementation of safety measures that minimize infection risk enabled by IoT sensors (temperature, humidity, CO2, and occupancy). Private, self-regulating behavior explains more than three-quarters of the decline in customer traffic in the restaurant industry due to customer's defense mechanisms to contracting the virus (Cronin & Evans, 2020). As these behaviors are self-restricted, effective communication on the implementation of safety measures can inform customers of the measures being taken to ensure their safety, and thus minimize those defense mechanisms.

Clear, direct, and science-based communication is effective in reassuring customers of their safety in a restaurant setting (Gomes de Freitas & Stedefeldt, 2020; Malecki et al., 2021). Customers who are informed with open, accessible, timely, and regular information on safety measures being undertaken during COVID-19 feel safer (Zhang et al, 2020). Social media posts about restaurants' sanitization procedures during COVID-19, for example, have been used strategically to show how the business is complying with current regulations (Gomes de Freitas & Stedefeldt, 2020). The perception of being informed about the pandemic reduces anxiety levels (Jungmann & Witthöft, 2020), with cognitive regulation as a significant moderator for this relationship. This, in turn, decreases perceived physiological risk and enhances safety (Tse et al., 2006). Thus, by informing customers of the implementation of sensors that measure ambient conditions and occupancy and how they contribute to a safer servicescape, we predict that the customers' self-regulating behavior will adjust, decreasing defense mechanisms, and consequently increasing their perceived safety in a restaurant setting (Figure 3.2).

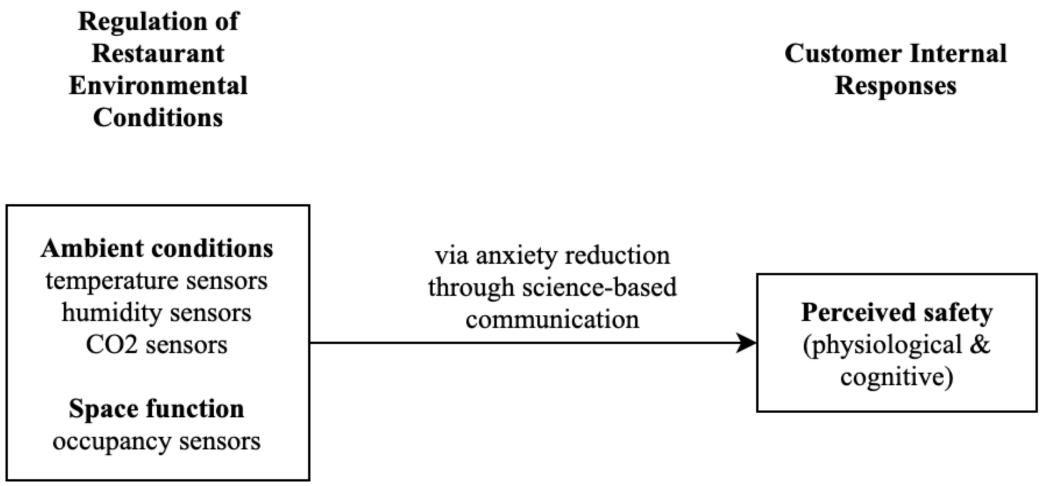

Figure 3.2. The effect of regulation of restaurant environmental dimensions through IoT sensors on customer perceived safety internal response

> **H2a.** Information about IoT sensors that measure ambient conditions in restaurants has a positive effect on customer perceived safety.

> **H2b.** Information about IoT sensors that measure occupancy in restaurants has a positive effect on customer perceived safety.

3.3 Customer Perceived Safety & Willingness to Visit the Restaurant

The perception of safety has been studied in contexts like urban public safety, quality of life, and personal satisfaction. Safety is considered as the most important factor when assessing public spaces, having a strong influence in the decision by the individual to make use of the space, or to avoid it (Mehta, 2014). Results are similar for indoor spaces, where safety influences the evaluation of the overall experience in the space, together with ambiance's comfort and social aspects (Haytko & Baker, 2004). In servicescapes, the perceptions of safety and pleasantness of the environment significantly increase satisfaction (e.g., Parish et al, 2008), willingness to pay (e.g., McDaniels et al, 1992), and approach-avoidance behaviors (e.g., Siguaw et al, 2019).

When individuals' need for safety is not satisfied, they are not motivated to engage in behaviors to meet their social needs (Maslow, 1943). Perceptions of risks that lead to feeling unsafe are subjective expectations of a loss that generate feelings of uncertainty, discomfort, and anxiety (Sweeney et al. 1999; Dowling & Staelin, 1994). Risk perception is an important determinant of behavior, especially in health behavior theories, and exhibits a high degree of consistency and strength of association with behavior across literature (Van der Pligt, 1996; Brewer et al., 2007). A meta-analysis on the impact of risk perception on customer purchase behavior revealed a negative relationship (Li et al., 2020). Thus, customers who perceive a high level of risk associated with shopping or purchasing will not engage in it. Because of the health risks associated with COVID-19, safety is a primary concern for customers, and thus the benefits of dining out must outweigh the negative health concerns for customers to take on the risk (Yost & Cheng, 2021).

Individuals that do not feel physiologically and cognitively safe during COVID-19 avoid close contact with other people, touching surfaces, and activities that they consider as non-essential, like going to restaurants. 27% of restaurant-goers would avoid dining out because they do not feel safe in restaurants (Klein, 2020). Due to the pandemic, customers are self-restraining to satisfy their basic need for food at home due to their perceived risks, making visiting a restaurant an unsafe option to the stay-at-home alternative. Thus, physiological and cognitive safety, a need that is usually met by restaurateurs in ordinary non-COVID times, becomes an essential need to satisfy in COVID-19 to make customers engage in what is perceived to be risky behavior, like visiting restaurants again (Aksoydan, 2007).

Making customers feel safe is essential to encourage their restaurant visits, because of the high-contact nature of services. Restaurants have the option to adapt their service offerings (Berry et al, 2020) to meet emerging customer needs for safety. Adaptation can be done by implementing new safety measures, like requiring face masks, deep cleaning of surfaces, and social distancing measures. As safety is a fundamental prerequisite during COVID-19, by increasing the perception of safety, customers can visit restaurants again. During COVID-19, feeling safe is synonymous with feeling protected from both physical and cognitive harm, both positive internal responses to the outside environment. Customer safety can then be regarded as a positive internal response to the servicescape which predicts approach behaviors, like the intention to visit a restaurant (Bitner, 1992).

> **H3.** Customer perceived safety has a positive effect on the customer's willingness to visit the restaurant.

3.4 Perceived Safety as a Mediator

Based on predictions derived from Bitner's framework on how a servicescape's environmental dimensions influence customer behavior, we similarly predict that the regulation of environmental dimensions through IoT sensors will affect willingness to visiting the restaurants by influencing customer perceived safety. As a focused derivation of Bitner's framework, customer perceived safety acts as the internal response mediator within a relationship between environmental dimensions and behavior that has already been studied and established by Bitner (1992).

Environmental psychology literature finds that customers respond to different dimensions of their physical surroundings cognitively, physiologically, and emotionally, and these responses to different environmental dimensions influence their approach behavior in the servicescape (Bitner, 1992). Thus, the regulation of environmental dimensions through IoT sensors is not expected to directly influence the customer's willingness to visit the restaurant. Instead, perceptions about environmental dimensions regulated through IoT sensors, formed through the information given by the restaurant, will lead to an internal response, which in turn, influences behavior (Bitner, 1992).

As shown elsewhere, the information about IoT sensors that regulate environmental dimensions will be concerned with communicating that the servicescape of the restaurant is a safe place to return to. Thus, we predict that the internal response will be a perceived safety response, because of the nature of information about IoT sensors, and that in turn, will increase the customer's willingness to visit. During COVID-19, customers are afraid to return to restaurants because they do not feel safe (Klein, 2020). Being safe is an element of internal responses usually not accounted for in research, because it is only experienced in its absence during high-risk times, like a global pandemic (Aksoydan, 2007). The effect of the regulation of environmental dimensions through IoT sensors on the approach behavior, willingness to visit the restaurant, will thus be mediated by the customer's internal safety response to the restaurant. This relationship is visualized in Figure 3.3.

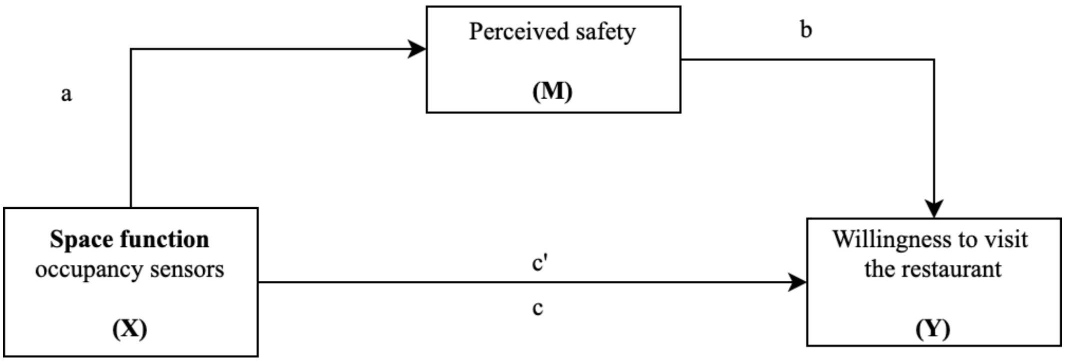

Figure 3.3. The proposed mediating effect of perceived safety in the relationship between information about ambient conditions through sensors and willingness to visit the restaurant.

Notes: *a is the effect of ambient sensors on perceived safety; b is the effect of perceived safety on willingness to visit the restaurant; c' is the direct effect of information about ambient sensors on willingness to visit the restaurant; c is the total effect of information about ambient sensors on willingness to visit the restaurant.*

> **H4.** Customer perceived safety mediates the effect of the regulation of environmental dimensions through IoT sensors on willingness to visit the restaurant.

3.5 Perceived Threat of COVID-19 as a Moderator

Generally, perceptions of risk vary with the person's attitude, risk sensitivity, and specific fear (Sjöberg, 2002). Consumers, thus, perceive the threat of COVID-19 differently. The perception of COVID-19 as a threat varies with age and employment status (Czeisler et al., 2020), personality traits like neuroticism (Liu et al, 2021), cyberchondria (Jungmann & Witthöft, 2020), interpretation, personal meaning attributed to the experience (Perez-Fuentes et al., 2020), and political ideology (Calvillo et al, 2020). The perceived threat of COVID-19 changes customer behavior and their evaluation of restaurants. For example, Kim & Lee (2020) show that customers who perceive the threat of COVID-19 as high, evaluate private dining rooms as their preferred dining option because they perceive these options as safer. Thus, similarly, heterogeneous perceptions of the risk of COVID-19 could lead to different customer's safety responses to a restaurant environment.

A recent study by Yang & Xin (2020) identifies three main heterogeneous consumer groups when it comes to risk perception amid the outbreak of COVID-19. Consumers differ in three main components of risk perception: (1) reason-based judgment on the possibility of being infected with COVID-19 (likelihood) (Brewer et al., 2007), (2) emotional perception of the severity of COVID-19 (severity), and (3) their belief that they can protect themselves from COVID-19 (protection efficacy) (Rogers & Prentice-Dunn, 1997). Based on the scores of these components, the heterogeneous groups are risk neutrals, risk deniers, and risk exaggerators. Risk neutrals comprise about half of the consumers and score moderately on all risk perception components. Risk deniers, 14% of the population, score low on likelihood and severity, but high on protection efficacy. Risk exaggerators, 35.8% of the consumers have high likelihood and high severity, but low protection efficacy (Yang & Xin, 2020).

The perception of being informed about the pandemic through science-based communication reduces anxiety levels (Jungmann & Witthöft, 2020), moderated by cognitive regulation. Reducing anxiety levels is critical to forming a safety perception in a restaurant. Risk exaggerators, however, usually rely on gossip and word-of-mouth to form risk judgments, judgments that then influence their high-risk perceptions (Yang & Xin, 2020). Thus, they might not be receptive to science-based communication, and thus it might not influence their risk perceptions. On the other end of the spectrum, risk deniers believe they are capable of high protection efficacy, which deactivates anxiety arousal (Bandura, 2007). Without any COVID-related anxiety present, the influence of cognitive regulation that comes from being informed with science-based communication might not take place (Jungmann & Witthöft, 2020) (Bandura, 2007). Due to their high perceived protection efficacy, risk deniers might not be currently shying away from public places like restaurants, and thus their perceived safety might not benefit from safety reassurance.

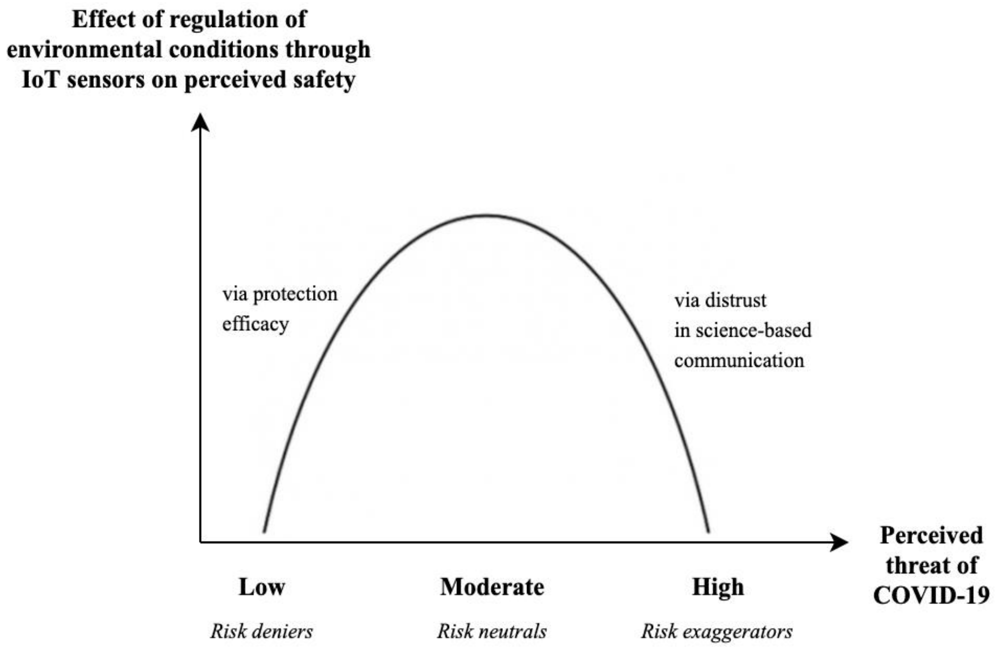

Figure 3.4. The proposed moderating relationship of the perceived threat of COVID-19 on the effect of regulation of environmental dimensions through IoT sensors on perceived safety

Thus, we argue that this heterogeneously perceived threat of COVID-19 can moderate the relationship between regulation of ambient conditions with IoT sensors (temperature, humidity, CO2, occupation) and the customer's perceived safety in a restaurant non-linearly (Figure 3.4). Only the customers that are moderately worried about COVID-19 can perceive the availability of ambient data through IoT sensors as a reassuring factor, more than customers who perceive the threat of COVID-19 as low or exaggeratingly high. The implementation of IoT sensors in a restaurant can have a greater effect on customers' internal safety response only for customers who feel moderately threatened by COVID-19. By communicating the sensor benefits related to risk perceptions of COVID-19, a regulated servicescape can enhance the risk neutral's perceived control and sense of security by lowering their anxiety levels.

> **H5**. The effect of the regulation of ambient conditions through IoT sensors on customer safety is poorest when the perceived threat from COVID-19 is at very low or very high levels.

4 Research Questions and Hypotheses

To summarize our discussion so far, the main research question of this thesis is the following:

"How does informing customers about the regulation of a restaurant's environmental dimensions through IoT sensors affect customers' intention to visit the restaurant?".

Based on recent technological advances and environmental psychology, servicescape and risk perception literature, we hypothesized the following:

H1a. Information about IoT sensors that measure ambient conditions in restaurants has a positive effect on customer willingness to visit the restaurant.

H1b. Information about IoT sensors that measure occupancy in restaurants has a positive effect on customer willingness to visit the restaurant.

H2a. Information about IoT sensors that measure ambient conditions in restaurants has a positive effect on customer perceived safety.

H2b. Information about IoT sensors that measure occupancy in restaurants has a positive effect on customer perceived safety.

H3. Customer perceived safety has a positive effect on the customer's willingness to visit the restaurant.

H4. Customer perceived safety mediates the effect of the regulation of environmental dimensions through IoT sensors on willingness to visit the restaurant.

H5. The effect of the regulation of ambient conditions through IoT sensors on customer safety is poorest when the perceived threat from COVID-19 is at very low or very high levels.

5 Method

This section describes the process used to gather and analyze the data needed for the testing of our hypotheses. We first give details on the sampling method and data collection procedure. Then, we describe the survey design and scale development.

5.1 Participants

The participants were adult restaurant-goers of all ages, genders, and dining habits. As this population counts more than 1,000,000 individuals on a global scale, the recommended sample size to obtain a 95% confidence level and variability of 50% to maximize variance is n = 384 (Gill & Johnson, 2010). Thus, we recruited a slightly higher number of respondents (n = 397) to capture a normal distribution of age, gender and education levels and obtain demographic data from a sample that was representative of adult restaurant-goers. The characteristics of the sample are summarized in Table 5.1 below.

Table 5.1. Demographics of Study Sample

	Factor	Total Sample	Social media	MTurk
	n	397	154	243
Gender	% Male	50%	32.9%	60.9%
	% Female	49.2%	65.2%	39.1%
	% Third gender	0%	0%	0%
	% Prefer not to say	0.5%	1.3%	0%
Age	18-25	30.2%	63.2%	9.1%
	26-35	36.8%	18.1%	48.6%
	36-45	10.8%	6.5%	13.6%
	46-55	10.1%	6.5%	12.3%
	56-75	11.8%	5.2%	16.0%
	Over 75	0.3%	0%	0.4%

The participants were recruited online using social media networks and Amazon's Mechanical Turk (MTurk). Various studies have shown that there is considerable similarity between treatment effects obtained from convenience samples using

MTurk and nationally representative population-based samples (Mullinix et al, 2015; Coppock & McClellan, 2019). On the other hand, participants recruited through social media made for a non-probability convenience sample. The combination of recruiting from social media and MTurk appeared as a reasonable compromise to collect representative results at a fair cost.

5.2 Design

To test our hypotheses, we conducted a quantitative online experiment to ensure the internal validity of the study. As the intention was to observe the effect of the regulation of ambient conditions through both ambient and occupancy IoT sensors, a within-subject design was the most appropriate to maximize response rates. An online experiment where the within-subject treatments are answered under the same conditions mitigates the threatening effect of history and maturation to the experiment's internal validity (Campbell, 1957). Further, by widening our respondent pool beyond a convenience sample, we aimed to mitigate some of the external population validity risks that come with experimental designs (Bracht & Glass, 1968).

The online experiment was programmed using Qualtrics. To reduce fatigue and survey drop-outs, the survey length was kept to around 7-9 minutes. To reduce misunderstandings and measurement errors (Reynolds, 1993) we tested the questionnaire with an initial pre-study ($n = 42$) to collect feedback on the survey flow and clarity of the questions. After making adjustments to the pre-study survey, we proceeded with the official data collection, sharing the survey on social media and distributing it via MTurk. The overall data collection took place during the first three weeks of March 2021. To ensure a normal distribution of age, genders, and education levels, we continuously monitored the demographics from MTurk participants and adjusted requirements for respondent characteristics to obtain better sample representativeness. We also rejected responses from M-Turk respondents that completed the survey in under two minutes as it signals a low level of attention to questions (Jun et al., 2007).

5.3 Procedure

To comply with the General Data Protection Regulation and Personal Data Act, the online survey began with a consent form that participants had to accept to proceed with the survey questions. All data were collected per BI Norwegian Business School guidelines for privacy. Thus, we did not collect data that could identify respondents' identity (IP address, geographical location, name, email).

First, the participants answered three questions related to their perceived threat of COVID-19. We then asked two additional questions regarding their risk sensitivity and their information sources during the pandemic. Risk sensitivity and information sources helped us determine which risk perception segment customers fall under. The participants were then introduced to a fictional restaurant, whose description is adapted from a description of popular restaurants (Kivela et al, 1999). We created a fictional restaurant to account for different attitudes participants might have towards an existing restaurant. We then assessed the customer's perceived safety in the restaurant and willingness to visit the restaurant without introducing any information regarding IoT sensors. This served as our control scenario to be later compared to the treatment scenario.

The subsequent question blocks introduced the two IoT sensors restaurant conditions under study: occupancy and air ambient sensors. We randomized the order of the two IoT sensor conditions questions to control for order bias (Malhotra, 2010). In the IoT ambient sensors treatment scenario, the restaurant informed the customers that it has introduced sensors that measure ambient conditions (CO2, humidity, temperature), followed by a short description of the sensors' benefits in the context of COVID-19, and was also supported with imagery (Figure 5.1). The customer's perceived safety and his/her willingness to visit the restaurant were then assessed. In the IoT occupancy sensors treatment scenario, the restaurant informed the customers that it has introduced sensors that measure occupancy, followed by a short description of the sensors' benefits for social distancing in the context of COVID-19, and was supported with imagery (Figure 5.2). The customer's perceived safety and his/her willingness to visit the restaurant were then assessed using the same scales as in the control scenario. Finally, participants answered questions related to gender, age, education level, restaurant dining habits, previous infection, and intentions to get the vaccination against COVID-19. The full questionnaire can be found in Appendix 11.1.

Figure 5.1. Imagery support for treatment scenario that introduced IoT ambient sensors

Figure 5.2. Imagery support for treatment scenario that introduced IoT ambient sensors

5.4 Measures

To create the constructs, we utilized scales used in previous research and made minor adjustments to better fit the context of the fictitious restaurant. All scales have thus already been measured for internal validity and reliability in previous studies (Appendix 11.2). Table 5.2 shows a full overview of the measurements and scales used for each construct. The scales used in the survey measure the perception of safety in restaurants, willingness to visit restaurants, the threat of COVID-19, perceived sensitivity to COVID-19, and information sources regarding COVID-19. The questions related to the threat of COVID-19, the control scenario, and the two IoT sensors scenarios were presented using a 7-point scale ranging from “strongly disagree” to “strongly agree”, except for the questions on sources of information used, that ranged from “never” to “always” on a 5-point scale.

For assessing the reliance on information sources regarding COVID-19, in the scale by Yang and Xin (2020), the Chinese websites Sina, Sohu, Weibo, and WeChat were replaced by more well-known websites in Western countries: Facebook, Instagram, Snapchat, TikTok, and Reddit. In the scale for assessing perceived safety by Hakim et al (2020) and Ngo et al (2020), general statements like "I believe it is safe to reopen restaurants", "I feel safe going to a restaurant" were replaced with the name of our fictitious restaurant, e.g. "I believe it is safe to reopen *Foodalicious",* "I feel safe going to *Foodalicious"*. Similarly, in the scale for willingness to visit the restaurant by Ryu et al (2012), statements like "I would consider revisiting this restaurant in the near future", "I would encourage others to visit this restaurant" were replaced by "I would consider revisiting *Foodalicious* in the near future", "I would encourage others to visit *Foodalicious* in the near future".

Table 5.2. Measurement scales used for latent variables.

Variable	Scale	Measurement	Source
Customer perceived safety	Likert 1-7	I feel safe going to *Foodalicious* to eat a meal.	Hakim et al., 2021
		I believe that it is safe to reopen *Foodalicious*.	Hakim et al., 2020
		I am sure that *Foodalicious* is reliable in terms of ensuring health safety.	Ngo et al., 2020
Willingness to visit the restaurant	Likert 1-7	I would go to Foodalicious with friends or family.	Ryu et al., 2012
		I would like to visit Foodalicious in the near future.	
		I would consider revisiting Foodalicious in the near future.	
		I would encourage others to visit Foodalicious in the near future.	
The perceived threat of COVID-19	Likert 1-7	Thinking about the coronavirus (COVID-19) makes me feel threatened.	Conway et al., 2020
		I am afraid of the coronavirus (COVID-19).	
		I am not worried about the coronavirus (COVID-19). *(r)*	
		I am worried that I or people I love will get sick from the coronavirus (COVID-19).	
		I am stressed around other people because I worry I'll catch the coronavirus (COVID-19).	
		I have tried hard to avoid other people because I don't want to get sick.	

5.5 Data Preparation & Reliability

Before conducting our analysis, we only excluded respondents who rejected consent to take the questionnaire. By rejecting consent, these respondents did not participate in the study and thus had no answers. This reduced the sample size from N=397 to N=392. We then reverse-coded measure items 3, 7, 8, 9, and 10 (Appendix 11.1) and computed new variables based on the measures of our online questionnaire (Table 5.2). The threat of COVID-19 was computed as the average score of six COVID-threat-related items for each participant. Similarly, the safety and willingness to visit scores for each scenario - control, visit, and ambient scenarios were computed by taking the reported average of the item scales that measured safety and visit for each respondent (Table 5.2). Finally, we computed the overall safety score and willingness to visit score by taking the mean of safety and visit scores in all scenarios. All scales had acceptable reliability (Cronbach's alpha > .75) (Santos, 1999) (Table 5.3).

Table 5.3. Reliability statistics for computed variables.

Variable	Cronbach's Alpha	N of items
Threat of COVID-19	.754	6
Perceived safety	.902	3
Willingness to visit	.901	4

5.6 Analysis

To observe the effect of information about IoT sensors on customer safety and visit, we first ran descriptive statistics to get an overview of the safety and visit mean scores in all scenarios and the perceived threat of COVID-19.

To test the first and second hypotheses, a one-way repeated measure analysis of variance (ANOVA) was conducted to evaluate the null hypotheses that there is no change in customers' perceived safety or willingness to visit score when measured before and after the introduction of ambient and occupancy sensors. Because there were only two treatment scenarios and the order in which the two treatment scenarios were shown to participants was randomized, some of the downfalls of using a repeated-measures ANOVA, like carry-over or fatigue, were mitigated (Girden, 1992). We then conducted follow-up pairwise comparisons to observe the significance of the pairwise differences between groups for both safety and visit (Kromrey & La Rocca, 1995).

To test the effect of perceived safety on customer's willingness to visit the restaurant, we ran linear regressions with the willingness to visit as a dependent variable and safety as an independent variable at the control scenario and two levels of treatment: ambient and occupancy. We then estimated the significance and valence of the unstandardized beta coefficient of safety on willingness to visit the restaurant at the three treatment levels.

Further, we used the PROCESS macro (Version 3) to test for a mediating effect of safety on the relationship between information about IoT sensors and willingness to visit the restaurant in both sensor scenarios: ambient and occupancy, thus testing Hypothesis 4. PROCESS is a macro that conducts observed-variable mediation, moderation, and conditional process analysis by using a multiple regression approach to mediation (Hayes, 2017). We created two new datasets where we restructured the data for ambient and occupancy sensors such that the presence of ambient or occupancy sensors was coded as 0 and 1 respectively. The PROCESS mediation analysis allowed us to see the total, direct and indirect effect of the presence of ambient and occupancy sensors on willingness to visit the restaurant, accounting for the mediating effect of perceived safety. PROCESS, therefore, serves as a direct statistical test for testing a mediation effect, in contrast to the four-step regression procedure outlined by Baron & Kenny (1986) which is stated in terms of descriptive non-zero coefficients. The four-step approach is not intended to test the statistical significance of the mediation effect (Wu & Zumbo, 2008), and the PROCESS macro was most appropriate for our goal.

To test for moderation, we first plotted the marginal means of safety in the occupancy and ambient sensors by the reported threat of COVID-19, which revealed a linear relationship. Thus, a linear mixed model analysis was deemed appropriate. To test the significance of the moderator through linear mixed model analysis, we utilized the restructured long form data from the mediation analysis such that the presence of ambient or occupancy sensors was coded as 0 and 1 respectively. The linear mixed model analysis is appropriate in experimental designs with random blocks because it accounts for the order effect and the individual differences in the use of scales (West et al., 2014). In these new datasets, the safety score served as the dependent variable, whereas the threat of COVID, occupancy, and ambient sensors, and their interactions served as covariates, and were assigned a fixed effect on the dependent variable. We also accounted for the participants' individual differences in using the scale by assigning the subject groups as a random effect. We ran individual linear mixed model tests for each covariate to predict the estimation effect of the covariates (ambient sensors and occupancy sensors respectively, and the threat of COVID-19) on the dependent variable, safety (West et al., 2014) and thus test for moderation.

We then expanded our analysis beyond our hypotheses to look at the significance and effect of variables outside of our predictive model on safety. These variables included demographic statistics, like age, gender, and education, as well as COVID-19-related variables, like information sources, vaccination, and infection. We conducted a General Linear Model (GLM) with safety as the dependent variable at the three levels of treatment. The levels of treatment were treated as within-subjects factors. The GLM allowed us to include several hypotheses regarding multiple criterion and contextual variables, observing possible effects of safety outside of our predictor variables (McNiel et al., 1996). Here, parameter estimates' unstandardized beta and significance were reported and observed.

Last, we aimed to create a final linear model that best estimated restaurant visits, which included both our model predictor variables and other contextual variables. Thus, we ran linear regressions and gradually excluded insignificant variables until we reached the highest levels of R-squared with significant predictors, thus obtaining the best goodness-of-fit of the linear regression line that predicted restaurant visits (Seber & Lee, 2012).

6 Results

6.1 Descriptive Statistics

The safety scores averaged 4.57 in the control scenario ($n = 395$), higher at 5.08 ($s = 1.47$) in the ambient sensors scenario ($n = 394$), and the highest at 5.17 ($s = 1.41$) in the occupancy sensors scenario ($n = 393$) (Table 6.1). On average, willingness to visit scores were higher than safety scores in all scenarios and were higher for the sensor scenarios than the control scenario. Compared to the control scenario ($n = 395$), the willingness to visit increased by 0.31 in the ambient sensor scenario ($n = 394$) and by 0.36 in the occupancy sensor scenario ($n = 392$) (Table 6.1). Finally, the mean threat of COVID-19 ($n = 396$), measured only once, was 4.54 ($s = .85$) (Table 6.1).

Table 6.1. Dataset descriptive statistics

Scenario	Variable	N	Mean	Std. Error	Std. Deviation
Control	Safety	395	4.5759	.07939	1.57779
	Visit	395	4.8578	.07346	1.45992
Ambient	Safety	394	5.0825	.07437	1.47614
	Visit	393	5.1690	.07181	1.42361
Occupancy	Safety	393	5.1747	.07160	1.41937
	Visit	392	5.2245	.06967	1.37930
Threat of COVID-19		396	4.5460	.04314	.85849

6.2 Hypothesis Results

6.2.1 Hypothesis 1

H1a. Information about IoT sensors that measure ambient conditions in restaurants has a positive effect on customer willingness to visit the restaurant.

A one-way repeated measure analysis of variance (ANOVA) indicated a significant effect of introducing ambient sensors on willingness to visit, where $Wilks' \ Lambda = .865, F(1{,}391) = 60.830, p < .001, \eta^2 = .135$ (Table 6.2). Follow-up comparisons suggested that the pairwise difference of willingness to visit in the control scenario and ambient sensor scenario was positive and significant, $(\mu_1 - \mu_2 = .321,\ p < .001)$ (Table 6.3). A boxplot of the mean difference of the reported willingness to visit in the control and ambient sensors scenario is illustrated in Figure 6.1.

Table 6.2. Wilks' Lambda from multivariate tests results on one-way repeated measure ANOVA for ambient and occupancy sensors effect on willingness to visit

Sensors	Value	F	Hyp. df	Error df	Sig.	Partial Eta squared
Ambient	.865	60.830	1	391	<.001	.135
Occupancy	.833	78.010	1	389	<.001	.167

Table 6.3. Pairwise comparisons of the mean difference of willingness to visit before and after the introduction of ambient and occupancy sensors.

Sensors	Mean difference	Std. Error	Sig.
Ambient vs. control	.321	.041	<.001
Occupancy vs. control	.370	.043	<.001

H1b. Information about IoT sensors that measure occupancy in restaurants has a positive effect on customer willingness to visit the restaurant.

A one-way repeated measure analysis of variance (ANOVA) indicated a significant effect of introducing occupancy sensors on willingness to visit, where $Wilks' \ Lambda = .833, F(1{,}389) = 78.010, p < .001, \eta^2 = .167$ (Table 6.2). Follow-up comparisons suggested that the pairwise difference of willingness to visit in the control scenario and occupancy sensor scenario was positive and significant $(\mu_1 - \mu_2 = .370,\ p < .001)$ (Table 6.3). A boxplot of the mean difference of willingness to visit in the control and occupancy sensors scenario is illustrated in Figure 6.1.

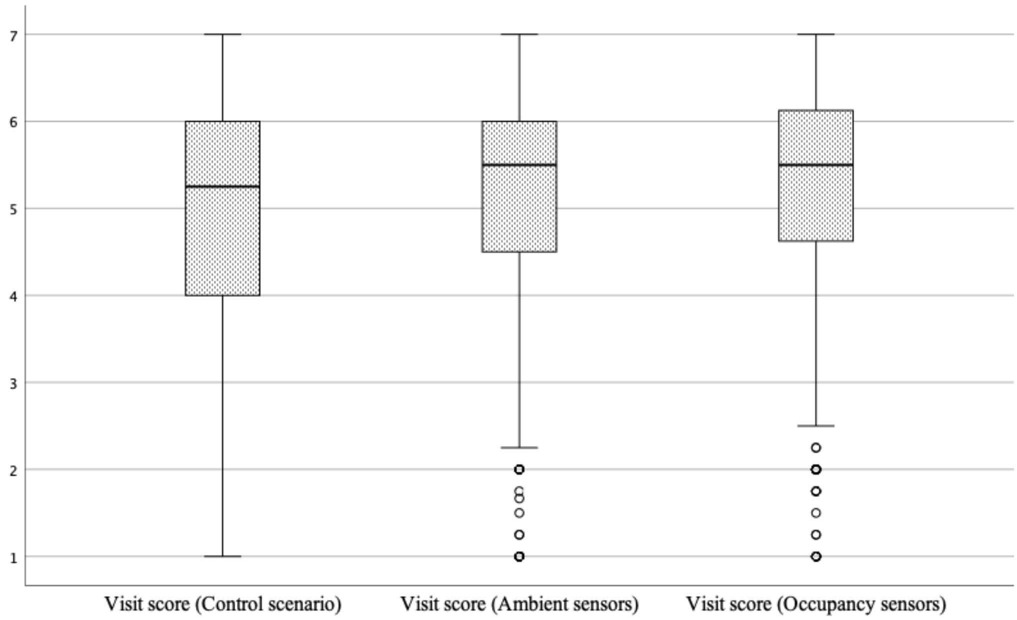

Figure 6.1. Boxplot of mean difference of willingness to visit in the control scenario, ambient sensors scenario, and occupancy sensors scenario.

6.2.2 Hypothesis 2

> **H2a.** Information about IoT sensors that measure ambient conditions in restaurants has a positive effect on customer perceived safety.

A one-way repeated measure analysis of variance (ANOVA) indicated a significant effect of introducing ambient sensors on perceived safety, where $Wilks' \, Lambda = .804, F(1{,}392) = 95.538, p < .001, \eta^2 = .196$ (Table 6.4). Follow-up comparisons suggested that the pairwise difference between perceived safety in the control scenario and ambient sensor scenario was positive and significant ($\mu_1 - \mu_2 = .508,\ p < .001$) (Table 6.4). A boxplot of the mean difference of perceived safety in the control and ambient sensors scenario is illustrated in Figure 6.2.

Table 6.4. Wilks' Lambda from multivariate tests results on one-way repeated measure ANOVA for ambient and occupancy sensors

Sensors	Value	F	Hyp. df	Error df	Sig.	Partial Eta squared
Ambient	.804	95.538	1	392	<.001	.196
Occupancy	.741	136.050	1	389	<.001	.259

Table 6.5. Pairwise comparisons of the mean difference of safety before and after the introduction of ambient and occupancy sensors

Sensors	Mean difference	Std. Error	Sig.
Ambient vs. control	.508	.052	<.001
Occupancy vs. control	.605	.052	<.001

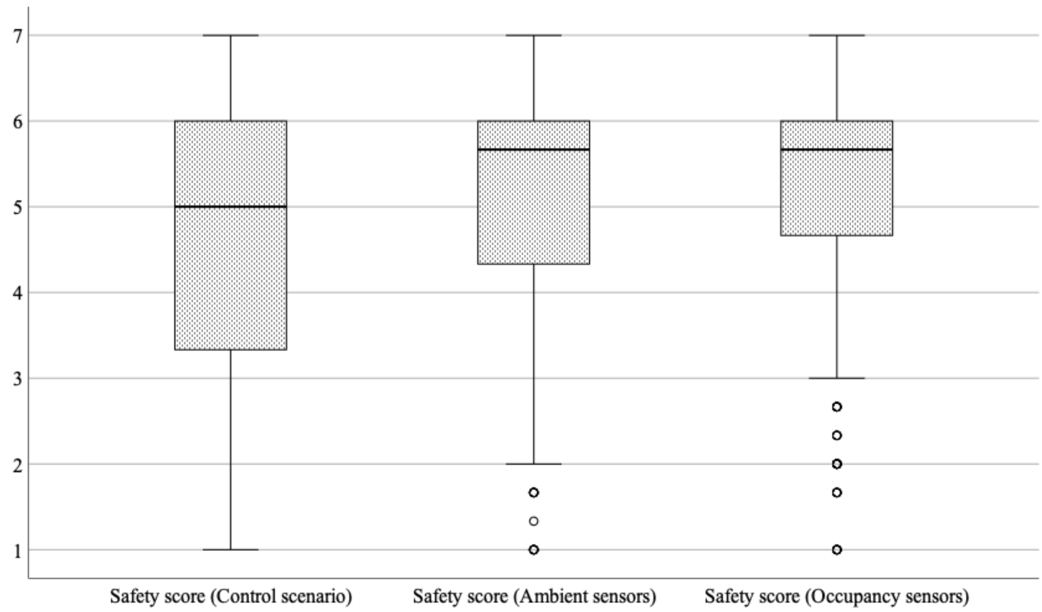

Figure 6.2. Boxplot of mean difference of perceived safety in the control scenario, ambient sensors scenario, and occupancy sensors scenario.

6.2.3 Hypothesis 3

H3. Customer perceived safety has a positive effect on the customer's willingness to visit the restaurant.

Before the introduction of sensors, when the customer's safety score is 0, the customer's willingness to visit is positive ($\alpha = 1.375, p < 0.01$) (Table 6.6). If the safety score goes up by 1 unit, the customer's willingness to visit will increase by .760 due to the safety effect ($\beta = .760, p < 0.01$), for a significant total score of willingness to visit from 1.375 to 2.135. The safety score explains 67.2% in the variation of the willingness to visit the restaurant ($R^2 = .672$) (Table 6.7). Figure 6.3 visualizes the relationship between the perception of safety and willingness to visit for the control scenario.

Table 6.6. Coefficient estimation for linear regression with the visit as the dependent variable and safety as the independent variable

Scenario		Unstandardized B	Coefficients Std. Error	t	Sig.
Control	Constant	1.375	.130	10.589	<.001
	Safety	.760	.027	28.352	<.001
Ambient	Constant	1.127	.146	7.721	<.001
	Safety	.796	.028	28.828	<.001
Occupancy	Constant	1.050	.150	6.985	<.001
	Safety	.805	.028	28.784	<.001

Table 6.7. Model summary for linear regression with the visit as the dependent variable and safety as the independent variable

Scenario	R	R Square	Adjusted R Square	Std. Error of the Estimate
Control	.820	.672	.671	.83735
Ambient	.825	.680	.679	.80628
Occupancy	.825	.680	.679	.78132

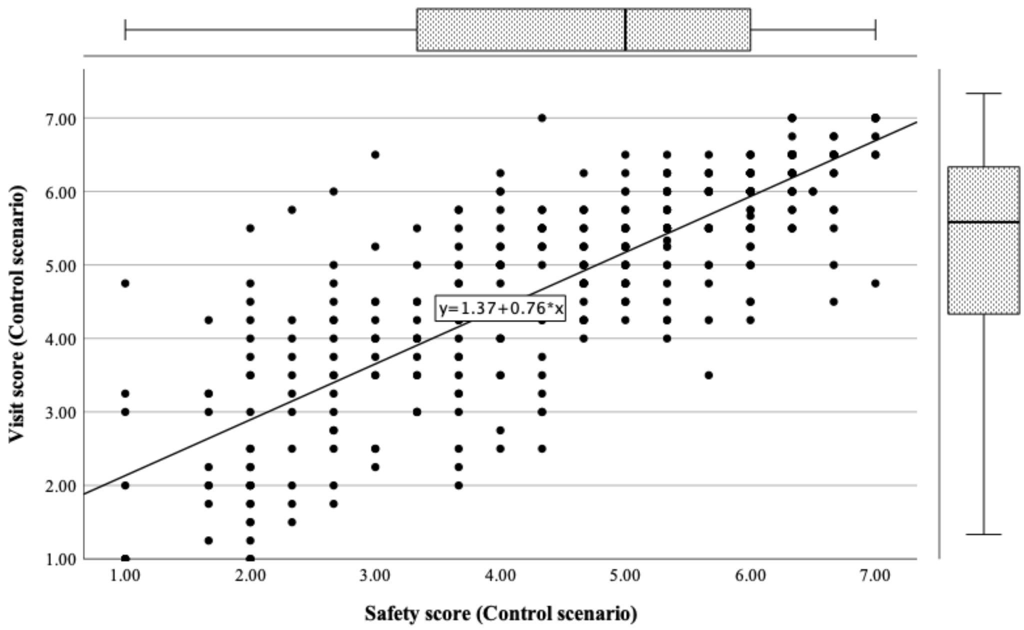

Figure 6.3. Regression plot of safety and visit scores in the control scenario.

After the introduction of ambient sensors, when the customer's safety score is 0, the customer's willingness to visit is 1.127 ($\alpha = 1.127, p < 0.01$) (Table 6.6). If the safety score goes up from 0 to 1, the customer's willingness to visit increases by .796 due to the safety effect from ambient sensors ($\beta = .796, p < 0.01$), for a significant increase in willingness to visit from 1.127 to 1.923. The safety score explains 68% in the variation of the customer's willingness to visit the restaurant ($R^2 = .680$) (Table 6.7). Figure 6.4 visualizes the relationship between the perception of safety and willingness to visit for the ambient sensors' scenario.

After the introduction of occupancy sensors, when the customer's safety score is 0, the customer's willingness to visit is 1.050 ($\alpha = 1.050, p < 0.01$) (Table 6.6). If the safety score goes up from 0 to 1, the customer's willingness to visit will increase by .805 due to the safety effect from occupancy sensors ($\beta = .805, p < 0.01$), for a significant total score of willingness to visit from 1.050 to 1.855. The safety score explains 68% in the variation of the customer's willingness to visit the restaurant ($R^2 = .680$) (Table 6.7). Figure 6.5 visualizes the relationship between the perception of safety and willingness to visit for the occupancy sensors scenario.

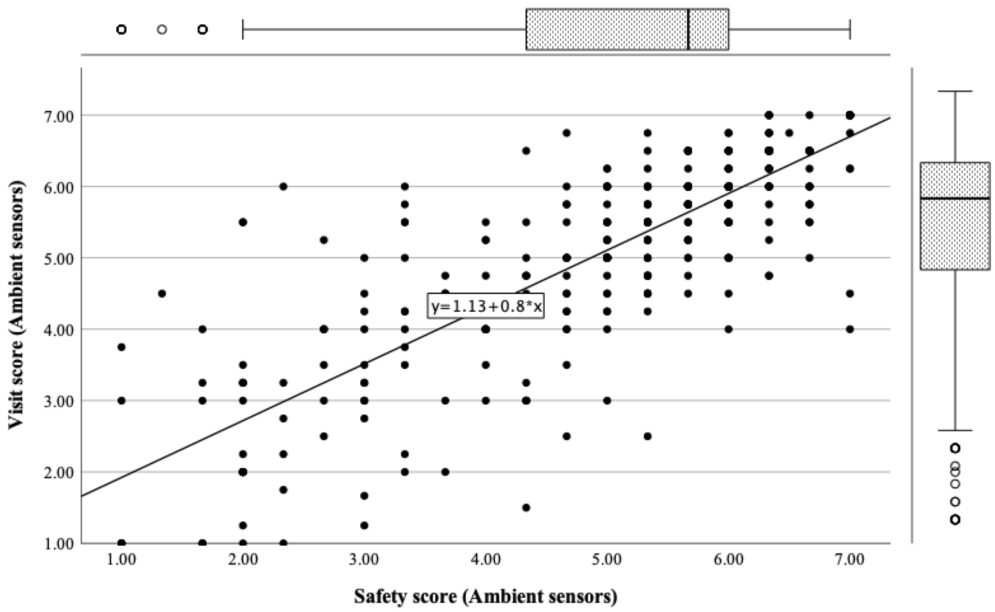

Figure 6.4. Regression plot of safety and visit in the ambient sensors scenario.

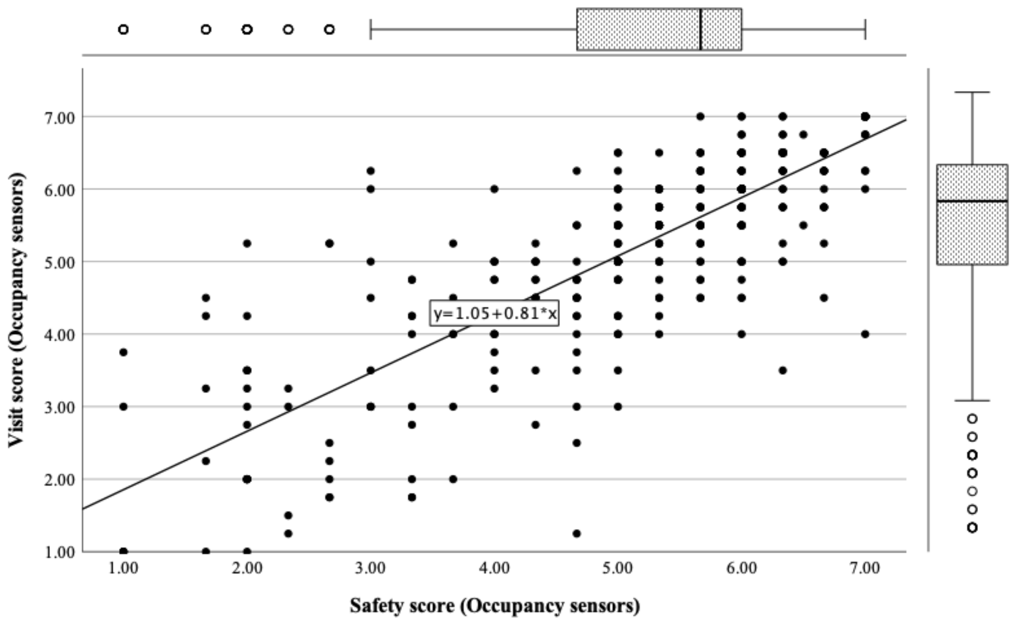

Figure 6.5. Regression plot of safety and visit in the occupancy sensors scenario

6.2.4 Hypothesis 4

> **H4.** Customer perceived safety mediates the effect of the regulation of environmental dimensions through IoT sensors on willingness to visit the restaurant.

Results from a simple mediation analysis with PROCESS indicated that information about ambient sensors is indirectly related to willingness to visit the restaurant through its relationship with perceived safety, with a total effect of information about ambient sensors on willingness to visit of X ($c = .341, p = .0023$). First, as can be seen in Figure 6.6, respondents' perception of safety scored higher when *ambient sensors* were present than when ambient sensors were not present ($a = .4963, p < .000$), and higher willingness to visit scores were subsequently related to higher safety perceptions ($b = .7767, p < .000$). However, after taking into account the ambient sensors' indirect effect through influencing safety, the ambient sensors' direct effect on safety proved insignificant ($c' = -.0714, p = .2295$). The full SPSS output can be found in Appendix 11.3.

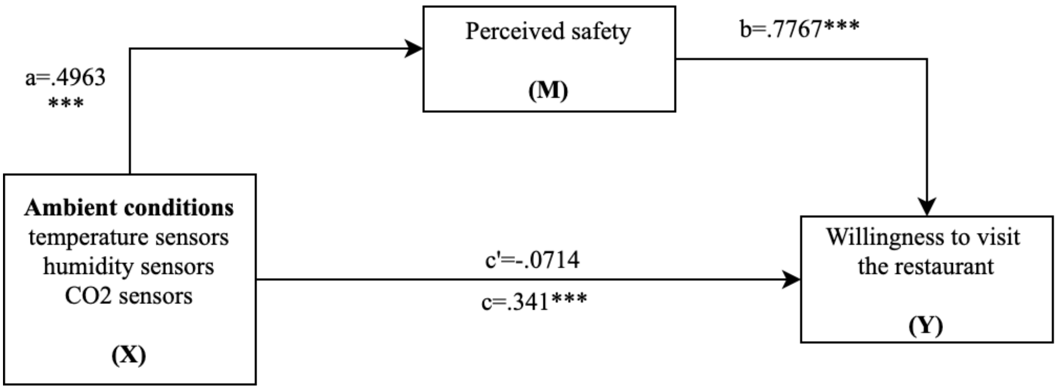

Figure 6.6. The mediating effect of perceived safety in the relationship between information about ambient conditions through sensors and willingness to visit the restaurant. *Notes*: ****p < .01*

Results from a simple mediation analysis with PROCESS indicated that information about *occupancy sensors* is indirectly related to willingness to visit the restaurant through its relationship with perceived safety, with a total effect of information about occupancy sensors on willingness to visit of X ($c = .3696, p = .0003$). As can be seen in Figure 6.7, respondents' perception of safety scored higher when ambient sensors were present than when ambient sensors were not present ($a = .6016, p < .000$), and higher willingness to visit scores were subsequently related to higher safety perceptions ($b = .7801, p < .000$). However, after taking into account the ambient sensors' indirect effect through influencing safety, the ambient sensors' direct effect on safety proved insignificant ($c' = -.0997, p = .0912$). The full SPSS output can be found in Appendix 11.4.

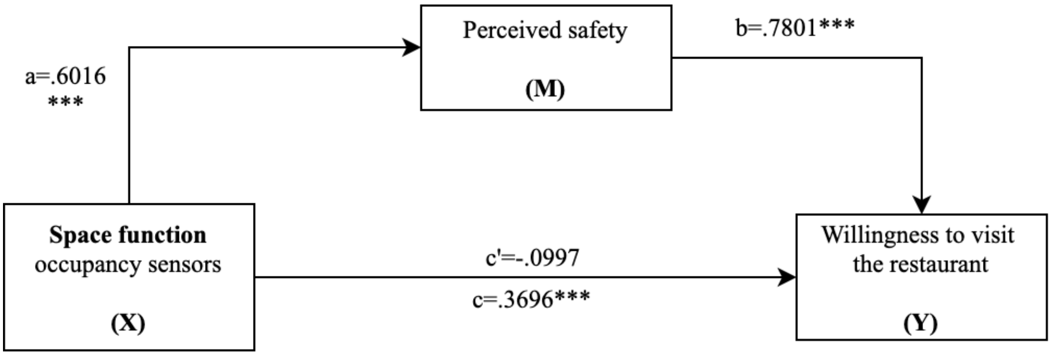

Figure 6.7. The mediating effect of perceived safety in the relationship between information about occupancy through occupancy sensors and willingness to visit the restaurant. *Notes*: ****p < .01*

6.2.5 Hypothesis 5

> **H5.** The effect of the regulation of ambient conditions through IoT sensors on customer perceived safety is poorest when the perceived threat from COVID-19 is at very low or very high levels.

A Type I test of fixed effects indicated that the intercept, ambient sensors, threat of COVID-19, and the interaction term are all significant covariates in predicting safety levels in the ambient sensors' scenario ($p < .05$) (Table 6.8). There is a positive interaction effect between ambient sensors and the threat of COVID-19 ($\beta = .06789$) (Table 6.9). An interaction effect chart (Figure 5-6) also suggests a positive and significant interaction term of ambient sensors and COVID-19 on top of a negative linear relationship between safety and threat of COVID-19.

Table 6.8. Type I Tests of Fixed Effects with Safety score as a Dependent Variable in the Ambient Sensors Scenario

Source	Num. df	Den. df	F	Sig.
Intercept	1	783	9174	.000
Ambient sensors	1	783	25.126	<.001
Threat of COVID-19	1	783	130.29	<.001
Ambient sensors * Threat of COVID-19	1	783	5.055	.025

Table 6.9. Estimates of Fixed Effects in the Ambient Sensor Scenario

Parameter	Estimate	Std. Error	t	Sig.
Ambient sensors	.506487	.108771	4.656	<.001
Threat of COVID 19	-.67042	.059759	-11.2	<.001
Interaction effect	.067898	.023358	2.907	.004

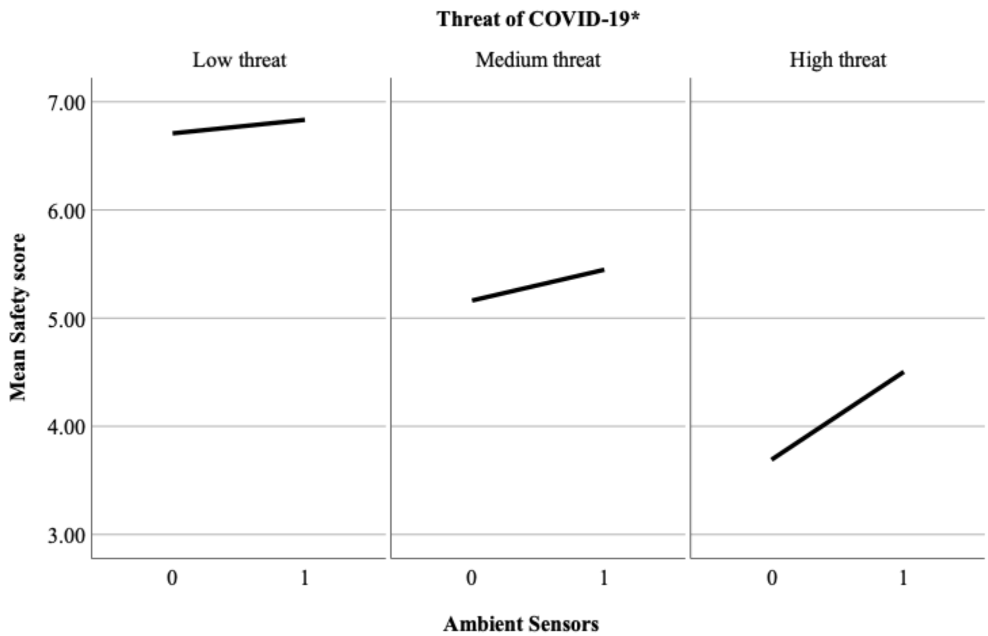

Figure 6.8. Interaction of the threat of COVID-19 and ambient sensors on safety

Notes: Threat scores are defined as follows: $Low\ threat = 1 - 2.3, Medium\ threat\ = 2.4 - 4.6, High\ threat = 4.7 - 7$

In the occupancy sensor scenario, a Type I test of fixed effects indicated that the intercept, occupancy sensors, threat of COVID-19, and the interaction term are all significant covariates in predicting safety levels ($p < .02$) (Table 6.10). There is a positive interaction effect between occupancy sensors and the threat of COVID-19 ($\beta = .09697$) (Table 6.11). An interaction effect chart (Figure 6.9) also suggests a positive and significant interaction term of occupancy sensors and COVID-19 on top of a negative linear relationship between safety and threat of COVID-19.

Table 6.10. Type I Tests of Fixed Effects with Safety score as a Dependent Variable in the Occupancy Sensors Scenario

Source	Num. df	Den. df	F	Sig.
Intercept	1	781	9738.07	.000
Ambient sensors	1	781	37.575	<.001
Threat of COVID-19	1	781	130.334	<.001
Ambient sensors * Threat of COVID-19	1	781	6.236	.013

Table 6.11. Estimates of Fixed Effects in the Occupancy Sensor Scenario

Parameter	Estimate	Std. Error	t	Sig.
Occupancy sensors	.605842	.106991	5.663	<.001
Threat of COVID 19	-.658277	.059282	-11.104	<.001
Interaction effect	.090697	.022954	3.951	<.001

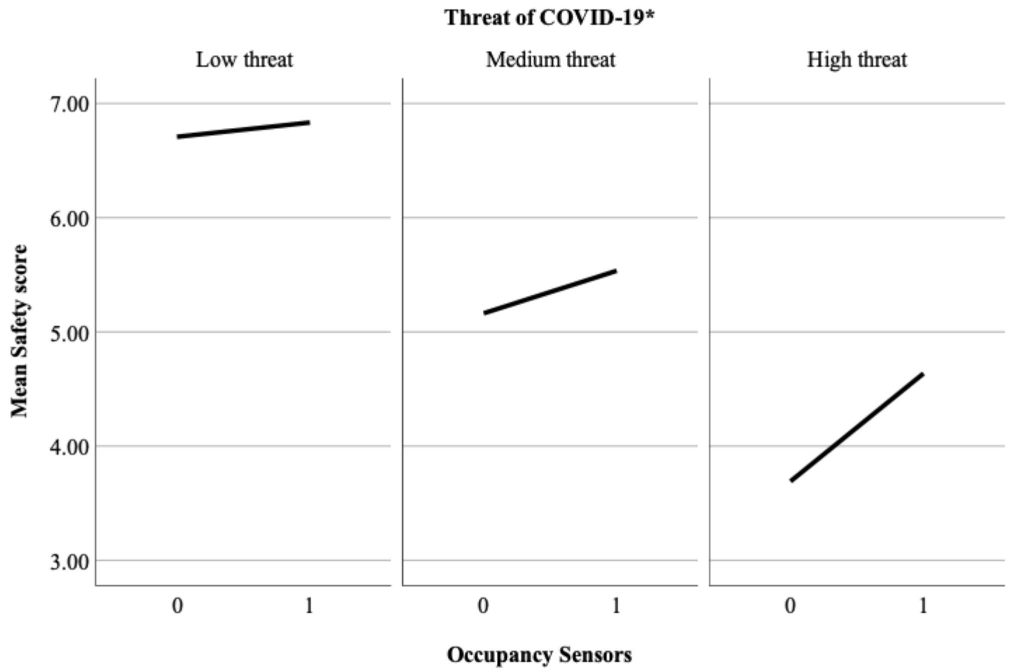

Figure 6.9. Interaction effect chart of the threat of COVID-19 and occupancy sensors on safety

6.3 Other Results

6.3.1 Contextual Variables Effect on Safety

A general linear model with safety as the dependent variable and all predictor and contextual variables as independent variables showed significant effects of age, education, dining frequency, infection, and gossip, social media, radio & tv as sources of information in some of the scenarios (Table 6.12). In the control scenario, education, dining frequency, infection, gossip as a source of information, and radio & tv as a source of information were all significant ($p < .04$). In the ambient sensors scenario, age, education, dining frequency, and infection were significant ($p < .03$). In the occupancy sensors scenario, age, dining frequency, and social media as an information source were significant ($p < .04$).

Table 6.12. GLM significant parameter estimates' effect on safety in all scenarios.

Dependent Variable	Parameter	Unstand-ardized B	Coefficients Std. Error	t	Sig.
	Intercept	3.388	.681	4.973	<.001

Dependent Variable	Parameter	Unstand-ardized B	Coefficients Std. Error	t	Sig.
Safety (Control)	Education	-.097	.048	-2.041	<.042
	Dining frequency	.293	.081	3.601	<.001
	Infection	-.212	.098	-2.163	.031
	Source: gossip	.270	.076	3.565	<.001
	Source: radio & TV	.147	.065	2.251	.025
Safety (Ambient)	Intercept	4.359	.661	6.597	<.001
	Age	-.157	.055	-2.873	.004
	Education	-.106	.046	-2.300	.022
	Dining Frequency	.349	.079	4.431	<.001
	Infection	-.241	.095	-.2534	.012
Safety (Occupancy)	Intercept	4.224	.640	6.595	<.001
	Age	-.183	.053	-3.441	<.001
	Dining frequency	.270	.076	3.537	<.001
	Source: social media	.146	.068	2.157	.032

6.3.2 Linear Model for Visit Predictions

The linear model with the best goodness-of-fit had the following significant predictors for restaurant visits: safety, social media as a source of information, the threat of COVID-19, and an interaction term for the threat of COVID-19 and safety in the presence of sensors. The linear model with estimated coefficients (Table 6.13) is:

$$Visit = 2.024 + .613 * Safety - .243 * COVID\_threat + .033 * Safety\_sensors * COVID\_threat + .124 * SoMe$$

This model accounts for 74.2% of the observed change in restaurant visits ($R^2 = .742$) (Table 6.14). Figure 6.10 shows the fitted regression line.

Table 6.13. Coefficient estimation for visit as a dependent variable

Variable	Unstandardized B	Coefficients Std. Error	t	Sig.
Constant	2.024	.546	3.71	<.001
Safety	.613	.087	7.082	<.001
Threat of COVID-19	-.243	.108	-2.249	.025
Safety (sensors) * Threat of COVID-19	.033	.017	1.969	.050
Social media	.124	.027	.128	<.001

Table 6.14. Model Summary for visit to the restaurant with constant, safety, the threat of COVID-19, safety*threat of COVID-19, and social media as predictors

R	R Square	Adjusted R Square	Std. Error of the Estimate
.862	.742	.740	.68948

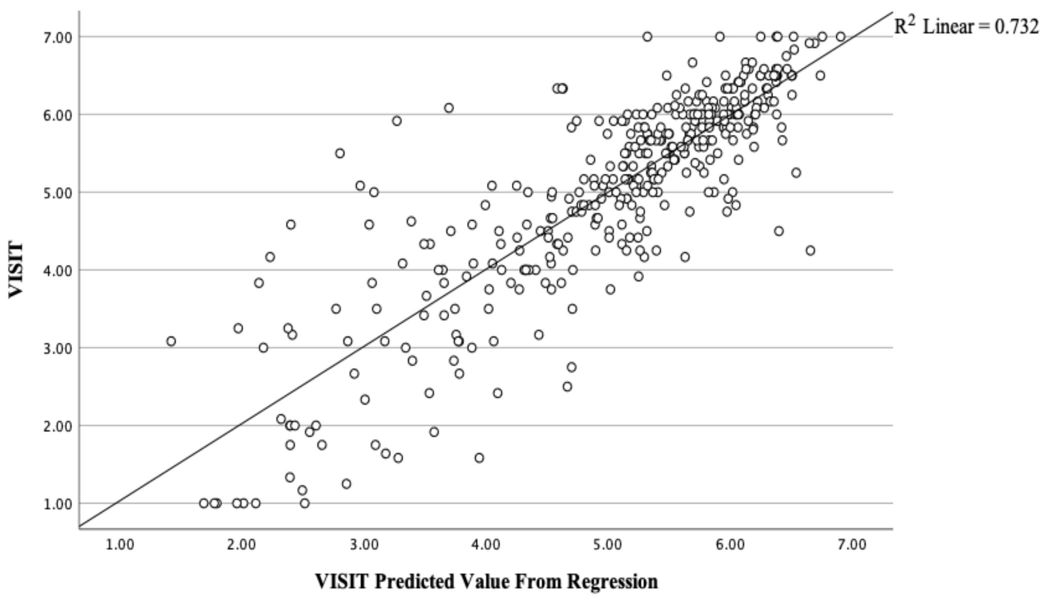

Figure 6.10. Regression predicted value vs. actual values for visit

6.4 Results Overview

Statistical evidence shows a significant increase in perceived safety and willingness to visit scores after the introduction of both ambient and occupancy sensors, suggesting that information about IoT sensors that measure ambient conditions and occupancy in restaurants increases both customer's willingness to visit the restaurant and customer's perceived safety. There is also enough statistical evidence to suggest a linearly positive effect of safety on customer's willingness to visit the restaurant in all scenarios. Further, information about both ambient and occupancy sensors is indirectly related to willingness to visit the restaurant through its relationship with perceived safety, with a positive total effect of information about ambient and occupancy sensors on willingness to visit. There was not enough statistical evidence to suggest a direct effect. Thus, Hypotheses 1, 2, 3, and 4 are supported. There is also statistical evidence to suggest that the threat of COVID-19 influences the safety perceptions before and after the introduction of sensors in the restaurant. However, the evidence suggests this relationship is negative and not U-shaped, as hypothesized. Table 6.15 below summarizes the overview of the results by hypothesis.

Table 6.15. Results Overview by Hypothesis

Hypothesis	Results
H1a	Supported by statistical evidence.
H1b	Supported by statistical evidence.
H2a	Supported by statistical evidence.
H2b	Supported by statistical evidence.
H3	Supported by statistical evidence.
H4	Supported by statistical evidence.
H5	Not supported by statistical evidence.

In the control scenario, education, frequency of restaurant visits, infection, and two sources of information, gossip and radio & TV were significant parameters for safety. In the ambient sensors' scenario, education, frequency of restaurant visits, and infection remained significant parameters for safety, but age also became significant, while sources of information became insignificant. In the occupancy sensors scenario, education and infection became statistically insignificant, while age and frequency of visits remained significant. In this scenario, social media as a source of information for COVID-19 was significant.

The model that best predicted willingness to visit the restaurant had the following significant predictors: safety (positive effect), the threat of COVID-19 (negative effect), social media as a source of information for COVID-19 (positive effect), and the interaction term of the threat of COVID-19 and safety in the presence of both sensors (positive effect).

7 Discussion

The outbreak of the COVID-19 pandemic led to serious challenges for business. In particular, restaurants have suffered from governmental restrictions like lockdowns and social distancing measures aimed at containing the spread of the virus. Restaurateurs, in response, had to come up with new ways to support their activities, e.g., providing their services through takeaways and home delivery options. Inspired by the emerging role of technology as a bridge to reduce the gap between businesses and customers, this study aimed to investigate how novel IoT sensors technologies can mitigate COVID-19 related risks and financial impacts.

Our findings show that informing customers about the adoption of IoT ambient and occupancy sensors in a restaurant has a positive effect both on their perceptions of safety and on their willingness to visit, in line with this study’s hypotheses. Communicating the presence of IoT ambient and occupancy sensors resulted in higher perceptions of safety and willingness to visit compared to the control scenario. Information about IoT sensors thus add a layer of safety to the servicescape elements (Bitner, 1992), encouraging approach behaviors. These findings support the previous literature on perceptions of safety (Cox, 1967; Lee, 2009), providing new applications for IoT technologies. Thus, this study shows that IoT sensors that measure ambient conditions and occupancy can help with the safe reopening of restaurants during COVID-19.

On the other hand, we did not find statistical support for the hypothesized U-shaped relationship between the customers' threat of COVID-19 and the effect of IoT ambient and occupancy sensors on customer safety perceptions. Contrary to predictions, the effect of the regulation of ambient conditions through IoT sensors on customers' perceived safety increases proportionally as the customer perceived threat increases. A possible explanation could be related to the customers’ levels of extraversion. Individuals with high levels of neuroticism and extraversion experience a higher perceived threat from COVID-19 (Liu et al, 2021). Thus, their inability to socialize because of the social distancing limitations might explain why some individuals feel more threatened by COVID-19 beyond anxiety levels. Additionally, extroverted individuals are also more likely to engage with service firms (Itani et al, 2020). Hence, for individuals who perceive the threat of COVID-19 as high, the perceived benefits of visiting restaurants could exceed the potential risks when measures like IoT sensors are communicated. It is also possible that information about IoT sensors could be an even more powerful tool than initially thought, able to encourage even people whose threat of COVID-19 is high.

We also found that IoT sensors that monitor occupancy have a greater effect than ambient sensors both on customers' perceived safety and their willingness to visit a restaurant. This might relate to social distancing now being commonly known as an effective measure to reduce virus spread. On the other hand, people might not have the same knowledge about the importance of monitoring air quality to limit COVID-19 spread, as generally governments do not communicate this safety measure to contain the virus spread. As the knowledge, practices, and attitudes that people hold towards COVID-19 determine the acceptance of measures to contain virus spread (Azlan et al, 2020), informing customers about scientific socially distanced occupancy appears more effective in increasing perceptions of safety, which in turn leads to higher willingness to visit a restaurant.

Another reason for this finding might be related to the degree to which individuals are actively involved in putting into practice measures against COVID-19. While customers need to actively participate in social distancing, they do not have to engage in the monitoring of air conditions. This might decrease the degree to which they feel involved and subsequently impact the trust in the effectiveness of the protective measure. The self-efficacy mechanism influences how people cope with changes in behavior and determines their level of physiological stress reactions (Bandura, 1982). It is easier for an individual to make sure that social distancing is respected, while ambient condition monitoring would mostly rely on trust in the restaurant. Thus, social distancing might be easier to accept and lead to lower levels of stress, increasing people's perceptions of safety and willingness to visit a restaurant more than regulation of ambient conditions.

Additionally, perceived safety was fundamental for the relationship between the communication of environmental dimensions and willingness to visit a restaurant to occur. As the direct effect of environmental dimensions on willingness to visit proved insignificant and slightly negative, communicating information about IoT sensors per se did not make customers more or less willing to visit a restaurant. However, the total effect on IoT sensors on willingness to visit through safety appeared significant and positive. Thus, information about IoT sensor benefits influences customers' willingness to visit a restaurant through influencing customers' perceived safety. Customers are more willing to visit a restaurant when their perceived safety increases, an increase which came due to information about IoT sensors. This falls in line with studies about perceptions of safety and behaviors when encouraging symbols (Espiner, 1999; Towner, 2019), like IoT sensors, are introduced. Encouraging signs usually promote approach behaviors by influencing a positive internal response to the restaurant (safety), also in line with Bitner's framework (1992). One example of encouraging signs as a safety signal is the presence of CCTV cameras in servicescapes, accompanied by reassuring communications about the safety of the space. This study similarly shows that introducing communications on IoT sensors can increase customers' willingness to visit the restaurant by increasing their perceptions of safety.

Another interesting finding is related to age, which proved significant in both IoT sensor scenarios but insignificant in the control scenario. As the effect of IoT sensors on customers' perceived safety decreases with age, older people showed lower levels of perceived safety than younger people when the restaurant communicated the use of IoT sensors. According to the Technology Acceptance Model (Davis, 1989), individuals' acceptance of technology depends on how useful and easy they perceive the technology to be. As technology interactions change with age as different generations show different usage, interests, and attitudes, the way users process information can affect trust differently (Herrando et al, 2019).

For example, people aged more than 65 years old account for only 7% of the total users online (Statista, 2019), indicating that there are still some barriers that limit their embracement of new technologies. Thus, this demographic group appears unlikely to be interested in IoT technologies, as also confirmed by the small number of people aged more than 60 that own an IoT device (Strother, 2017). Additionally, there is generally low awareness around the concept of IoT. A study on the adoption of IoT technology showed that across people using at least one type of IoT device, 78% of them are not aware of the Internet of Things concept (Macik, 2017). This might indicate that by changing the name of our sensors in the study to more generally recognized technologies like Wi-Fi and Bluetooth, we could have found better perceptions of safety among older generations due to increased familiarity with the technology.

Education appeared as a significant predictor for perceived safety in the control and IoT ambient sensors scenario, but not in the occupancy sensors scenario. This could be related to the widespread social distancing measures being undertaken, thus suggesting that being highly educated does not play a role in understanding the implications of IoT occupancy sensors on safety. The negative effect of education in the control scenario suggests that the higher the level of education for customers, the less safe they feel in a restaurant. This might be explained by the fact that a higher level of education is usually associated with less adherence to misinformation that undermines the threat of COVID-19. A study showed that only 15% of people with a postgraduate degree find some truth in conspiracy theories, compared to 48% of people with a high school diploma or less (Schaffer, 2020). Thus, individuals with high educations levels are less likely to undermine COVID-19 related risks. This might also explain the negative effect of education in the IoT ambient scenario, suggesting that highly educated individuals are less likely to trust IoT ambient sensors' effectiveness in reducing the likelihood of infection because of a higher level of skepticism.

Another significant predictor across both IoT sensors and control scenarios for perceived safety was the dining frequency, with a positive effect. People that often dine out are more likely to feel safe in a restaurant. This might be explained by the framing of our question, where we invited respondents to imagine *Foodalicious* as a downtown restaurant in their area where they often have dinner. This could have contributed to a sense of familiarity and attachment that led to pleasant feelings of comfort. Place attachment, the development of an affective bond between individuals and places (Hidalgo & Hernandez, 2001), is expressed both through emotions and behaviors (Altman & Low, 1992) with a desire to remain close. Thus, familiarity with the place reduces uncertainty and increases comfort, probably influencing perceptions of safety.

Additionally, sources of information on COVID-19 present other interesting findings. In the control scenario, gossip and radio/TV have a significant and positive effect. Gossip in particular has a highly positive effect, suggesting that people that rely on this source of information are more likely to feel safe in a restaurant. However, in contrast with previous research, gossip and radio/TV were more associated with risk deniers rather than risk exaggerators. Radio and TV as sources of information might undermine threats related to COVID-19 to reassure public opinion and spread the message that everything is under control. On the other hand, gossip from friends might increase the perception of safety because of the low reliance on scientific information, in an attempt to boost optimism around the pandemic. In the IoT ambient sensors scenario, sources of information become insignificant, while in the occupancy sensor scenario, social media is significant and has a positive effect on perceived safety. Contributing to this finding might be the likelihood to read information about social distancing and its effectiveness on social media compared to air quality monitoring. Additionally, the spread of misinformation on social media, which often undermines potential risks, might influence people's perceptions of threat (Malecki et al, 2021).

We also found a positive influence of social media as a source of information about the COVID-19 pandemic, which was statistically linked to a higher willingness to visit restaurants. The more frequent use of social media as a source of information during the COVID-19 pandemic has been linked to higher anxiety levels concerning the pandemic and individuals who exhibit high anxiety in general (Gao et al., 2020). High anxiety levels have been subsequently linked to risk exaggerators, defined as individuals with the high perceived threat of COVID-19 in our study. Risk exaggerators responded the most positively to information about IoT sensors but showed the lowest willingness to visit scores out of all groups. Thus, there could be a reason beyond high anxiety levels that link the use of social media as a source of information about the COVID-19 to willingness to visit scores. An interesting direction to look at concerns the role of influential individuals using social media. Public figures like scientists or politicians might spread the message that the situation is under control and legitimate visiting public spaces like restaurants during COVID-19 (Malecki et al, 2021). Further, people on social media tend to follow others that they like, often in the context of political preference. Therefore, they are more likely to trust these sources (Malecki et al, 2021; Sandman, 2006) and limit exposure to other political views. This belief-consistent selection might lead people to visit restaurants after seeing others do the same through social media (Hills, 2018; Chater and Loewenstein, 2016).

8 Recommendations

8.1 Strategic recommendations

A majority of people might not be willing to dine in at restaurants immediately when they will reopen (Gursoy & Chi, 2020). Thus, restaurateurs need a new approach to market their services. As perceptions of safety predict the intention to visit a restaurant, restaurateurs should switch their marketing strategies to include safety communications. Given a large number of restaurant-goers still do not feel safe to dine out, marketing communications with a focus on the measures that the restaurant is undertaking to ensure customer safety will be effective in increasing customers' willingness to visit the restaurant. Customers respond positively to science-based communication around pandemic-compliant behavior, and the communication of the introduction of IoT sensors to the servicescape is a good strategy to align with behavior that reassures customer safety.

Restaurants should also shift their marketing strategy to account for all dimensions of the servicescape, even those that are not picked up by senses. While space layout regarding social distancing is a visible change to the servicescape, non-visible elements, like ambient conditions, should also be considered, especially in the context of a pandemic. These servicescape dimensions include temperature, CO2, humidity, and air ventilation. They are all important elements that should be optimized based on data gathered through sensor technology to ensure a safer environment for restaurant-goers. These dimensions, when optimized and communicated in a benefit-driven way will make customers feel safer. Further, as most restaurants are now implementing some form of table social distancing to ensure compliance with governmental regulations, focusing on the communication of an additional safety dimension, that of ambient conditions, might prove a competitive advantage in a time where safety compliance communications should be placed at the forefront of marketing strategy.

IoT sensors that regulate environmental dimensions and increase customer perceived safety can be the foundation of strategic planning for future epidemics or pandemics, thought to be more frequent and severe in the future (Dodds, 2019; Chin et al, 2020). As public spaces close and similar social distancing measures are put in place in future pandemics, restaurants must have a strategy in place to respond to future regulations and mitigate customer risks and fears. In this direction, Gomes de Freitas & Stedefeldt (2020) outline five stages of building active resilience to manage future pandemics: (1) planning and preparation, (2) absorption, (3) recovery, (4) adaptation, and (5) building the future today. As of the writing of this thesis, we are currently in the recovery stage, as Western countries reopen, and vaccinations roll out. IoT sensor technology can be implemented and incorporated in each stage of the resilience-building process, thus creating the foundation for a strategic plan to handle future pandemic and epidemic scenarios.

Data from IoT sensors that gather information about environmental dimensions can also be used beyond COVID-19, as the world returns to normalcy. While in the context of the pandemic, the goal is to use the data to reassure customer safety and subsequently increase their willingness to visit the restaurant, managers should also consider how to use the data beyond COVID-19. Temperature, humidity, and CO2 data can ensure that ambient conditions are always optimized to ensure a healthy servicescape, and occupancy sensors can give insight into how customers and employees use the restaurant space. Further, both types of sensors can reveal insights about whether the elements of the servicescape they measure are helping or hindering customers and employees to complete their goals. For example, occupancy sensors can become the basis of a space occupancy heatmap that reveals insights about the flow of customers and employees in the restaurant, and whether the design of the space follows the flow of servicescape user movement. Thus, IoT sensors can provide value to the restaurant servicescape beyond the pandemic.

8.2 Research implications

Our study adds novelty to Bitner's servicescape framework due to its incorporation of the safety element. Literature on perceived safety regarding the servicescape is non-existent, mainly due to a lack of need thus far for a shift in focus. Perceived safety is an internal response to the service environment which was taken for granted before the COVID-19 pandemic. However, the considerations of the risks and benefits of dining out with regards to feeling safe have now become a barrier to restaurant visits. Thus, by incorporating the arising need to account for these changing internal responses of safety to the servicescape, we provide a foundation to study the relationship of a restaurant's servicescape element with the current and future customer behaviors that may arise due to the disruption of safety. These scenarios could be future epidemics or pandemics, or other unprecedented times of high collective anxiety.

This study also makes a leap in terms of marketing communications for IoT technologies and the COVID-19 pandemic. We found that communications revolving around IoT technologies are effective in increasing perceived safety and subsequently willingness to visit restaurants. Our findings on social media as a source of information about COVID-19 and its link to higher willingness to visits also add a dimension to the use of social media as a marketing communication tool in the context of the pandemic.

Further, this is one of the first marketing studies to implement novel technologies into Bitner's servicescape framework (1992). Most studies on novel IoT technologies are concerned with data privacy elements and customer behavior for IoT technologies that are sold as products and services, e.g., wearables or virtual assistants (Nguyen & Simkin, 2017). No study has looked at customer behavior in relation to adjustments to the environmental dimensions of a servicescape as a complementary service through technology. Some studies that do, take a value co-creation approach, where the object of study is "smart servicescapes" and the creation of value from the technology in collaboration with customers (e.g., Roy et al., 2019, Balaji & Roy, 2017). As our society is heading towards the smart cities and smart servicescapes of the future, our adapted framework could be a good starting place for the further study of the regulation of the environmental elements of servicescape through novel technology.

8.3 Limitations

This study has some potential limitations with the selection of participants and the adoption of the servicescape framework. The results of this study are therefore subject to biases that might have influenced estimates. Despite our best efforts to collect representative data, using social media and M-Turk to recruit participants might lead to lack of diversity in the recruitment pool (Goodman et al., 2013). Thus, there might be limitations in the generalizability of the data to all restaurant-goers. Further, the fictitious restaurant described in the online experiment is based on the description of a popular sit-down restaurant, limiting the ability of our framework to make predictions about other types of restaurants. Our research framework also omitted the influence of employee activities and their internal responses to the servicescape, as well as their interaction with customers. This might have therefore led to an incomplete picture regarding safety perception predictions.

8.4 Directions for future research

The popularity of introducing IoT sensor technology to servicescapes is on the rise and future epidemics or pandemics are predicted to become more frequent in the future. Thus, there is an overarching need to establish a body of work in Marketing that is concerned with the integration of novel technologies into the servicescape. Specifically, more research is needed in IoT sensor technology's ability to influence a servicescape's environmental dimensions, and how that, in turn, influences customer behavior. Future studies could build on our findings to address the intricacies of a marketing communication strategy about both IoT technologies and future pandemics. Our framework could also be completed to include the interaction between customers and employees in future research.

The study of IoT technologies in relation to the servicescape does not have to be bound to the restaurant industry, or ambient and occupancy sensors. It would be interesting to further look at whether an increase in safety and willingness to visit the restaurant due to the communication of the value of IoT sensors could be replicated in different service industries or with other kinds of sensors. For example, the value of the regulation of ambient conditions through IoT sensors could take a different meaning in a retail, travel, or personal services setting. Future research could also look at the effectiveness of different types of IoT sensors in different industries depending on the interpersonal interaction needed, the necessity of the service, and the amount of risk associated with the service.

Although the literature on the threat of COVID-19 links high perceived levels of threat with risk exaggerators, who exhibit high anxiety levels and are often ill-informed, this study shows that these groups are receptive to science-based communication. Information about IoT sensors changed perceived safety levels the most in risk exaggerators, thus casting doubt on previous assumptions and findings about this customer segment. Future studies could investigate the relationship of the high level of anxieties, risk sensitivity, and extraversion in the context of restaurant visits, and look at the mechanisms behind why risk exaggerators feel safer in the presence of this technology in restaurants, contrary to initial predictions.

9 Conclusions

As one of the most financially burdened industries due to the COVID-19 pandemic, the restaurant industry needs to find more effective ways to encourage customers to return to dining out. Despite vaccination rollouts and increased safety measures, customers might not be returning to restaurants because they are afraid for their health. The objective of this thesis was to propose a new way to encourage customer visits to restaurants at the time of the COVID-19 pandemic. Inspired by the novel IoT sensor technologies being adopted to ensure workplace safety across other industries, we introduced the role of these technologies in the context of a restaurant's servicescape and the COVID-19 pandemic. Drawing from the servicescape and risk perception literature, we hypothesized that information about the regulation of ambient conditions through IoT sensors would increase customers' willingness to visit restaurants by increasing customers' perceived safety. We also argued that the effect of the information about the regulation of environmental dimensions through IoT sensors on customers' perceived safety was moderated by the customers' perceived threat of COVID-19. Our study revealed that:

- Information about IoT sensors that regulate the restaurant's environmental dimensions (ambient conditions and occupancy) increases customers' willingness to visit the restaurant indirectly by increasing their safety perceptions about the restaurant's servicescape. There was no direct effect of information about IoT sensors that regulate environmental dimensions on customers' willingness to visit the restaurant.
- Information about IoT sensors that regulate the restaurant's occupancy, i.e., occupancy sensors that encourage social distancing, have a greater positive effect on the customer's willingness to visit the restaurants than information about IoT sensors that regulate the restaurant's ambient conditions, i.e., temperature, humidity, and CO2 sensors.
- The customers' perceived threat of COVID-19 linearly and positively moderates the relationship between information about IoT sensors that regulate the restaurant's environmental dimensions and customer's perceived threat. Thus, the higher a customer perceives the threat of COVID-19, the more effective information about IoT sensors that regulate environmental dimensions is at increasing customer perceived safety.
- Factors that influence the customer's willingness to visit the restaurant in all scenarios were perceived safety (positively), the threat of COVID-19, perceived safety when sensors were present given their perceived threat of COVID-19 (positively,) and social media as a source of information about COVID-19 (positively). These factors altogether explained 74% of the variation in willingness to visit across all customers in all scenarios.

As our study shows, implementing and communicating the value of novel IoT sensor technologies is an effective way to ensure customers feel safe and thus return to restaurants. In this respect, both sensors that measure ambient conditions and occupancy can help. Certain levels of temperature, humidity, and CO2 levels in the air have been previously linked to COVID-19 transmission levels. A distance of further than one meter between people has also been demonstrated to decrease the likelihood of virus transmission. Restauranters can ensure a safer space for customers by measuring and regulating these environmental dimensions.

Our study shows that communicating these efforts is effective in increasing the customer's willingness to visit the restaurant indirectly by making them feel safer. Information about the benefits of IoT sensors does not influence the customer's willingness to visit directly on its own. Instead, it increases the customer's perceived safety, which then increases their willingness to visit the restaurant. This increased safety and willingness to visit the restaurant due to the communication of benefits of IoT sensors is effective independent of the customer's perceived threat of COVID-19. However, it proves most effective in customers that experience high levels of the perceived threat of COVID-19. Thus, the technology is effective in reassuring even customers that have so far avoided public spaces in an attempt to follow all COVID-19-related regulations.

Science-based communication with a focus on what is an already familiar measure of infection spread seems to have better results in reassuring customers that the restaurant is compliant with regulations and is a safe place to return to. Social distancing is a measure to slow down or stop the spread of the pandemic that is widespread and highly familiar across customers in all countries. All countries that have experienced the COVID-19 pandemic incorporated some form of social distancing into their governmental regulations, rooted in scientific studies for pandemic influenzas (e.g., Glass et al., 2006; Caley et al., 2007). A COVID-19 study by Greenstone & Nigam in March 2021 showed that three to four months of moderate distancing would save 1.7 million lives by October.

Further, social distancing measures are the most communicated by national and international media outlets, thus customers are most familiar with them. On the other hand, measures pertaining to ambient conditions like humidity, temperature, and CO2 are not very well-known. Ambient conditions have only been discussed in the mainstream in the context of air safety and air ventilation in airplanes (e.g., Read, 2020; Fox, 2020; Gröndahl et al. 2021). This high familiarity with social distancing measures could explain why information about IoT occupancy sensors is more effective than information about ambient sensors in increasing customer's safety, and subsequently increasing their willingness to visit the restaurant.

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11 Appendix

11.1 Full questionnaire

Block	Measurement	Scale
Consent form	Hello and thank you for deciding to take part in our online experiment. This online experiment is constructed as part of the process of primary data collection for the completion of a Master's Thesis in the Strategic Marketing Management Program at BI Norwegian Business School. The procedure involves filling an online questionnaire that will take approximately <u>9 minutes</u>. Your responses will be confidential, and we do not collect identifying information such as your name, email address, or IP address. We will only use the data provided for the purpose specified in this consent form. We will process your data confidentially and in accordance with data protection legislation (the General Data Protection Regulation and Personal Data Act). If you have any questions about the research study, please contact the MSc. students responsible for this research, Ms. Megi Hamza (megi.hamza@student.bi.no) or Ms. Anthea Bellavista (anthea.bellavista@student.bi.no). ELECTRONIC CONSENT: Please select your choice below. Clicking on the "Agree" button below indicates that: • You have read the above information • You voluntarily agree to participate. • You are at least 18 years of age If you do not wish to participate in the research study, please decline participation by clicking on the "disagree" button.	• Disagree (0) • Agree (1)

Block	Measurement	Scale
Block 1: Measuring the degree of perceived threat of COVID-19	***Q1***. Given your current perception of COVID-19 related risks, to what extent do you agree with the following statements: 1. Thinking about the coronavirus (COVID-19) makes me feel threatened. 2. I am afraid of the coronavirus (COVID-19). 3. I am not worried about the coronavirus (COVID-19). 4. I am worried that I or people I love will get sick from the coronavirus (COVID-19). 5. I am stressed around other people because I worry I'll catch the coronavirus (COVID-19). 6. I have tried hard to avoid other people because I don't want to get sick. 7. It would be better to go back to normal, even if some people die. 8. If my friends or family are not isolated during the pandemic, I also do not need to be isolated. 9. There is no point in avoiding the coronavirus now and catching it later. 10. I am not afraid of contracting the disease; it is simply the flu.	• Strongly disagree (1) • Disagree (2) • Slightly disagree (3) • Neutral (4) • Slightly agree (5) • Agree (6) • Strongly agree (7)
	Q2. How often have you relied on the following sources within the previous two weeks to obtain information about the Coronavirus (COVID-19)?	• Never (1) • Sometimes (2)

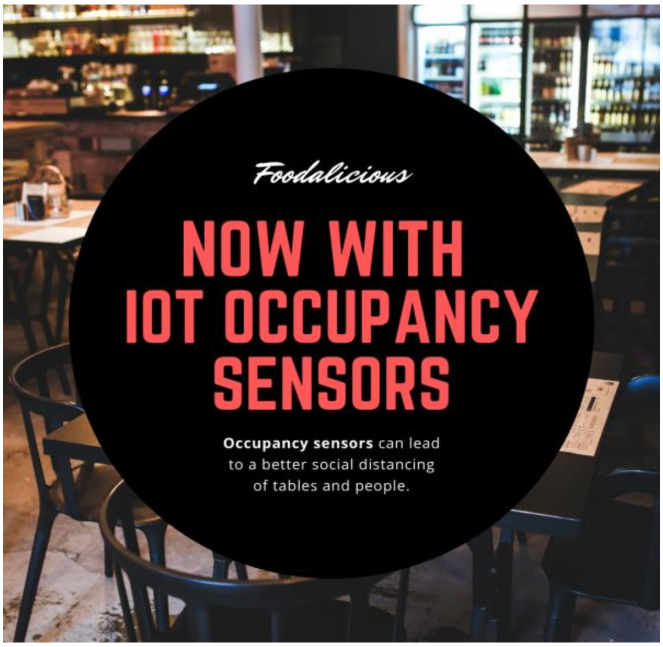
Block	Measurement	Scale
	11. central and local radio or television stations 12. central and local government websites 13. central and local newspapers and their websites 14. Facebook, Instagram, Snapchat, TikTok, or similar social media 15. Reddit or similar online communities 16. gossip, news spread among friends.	• About half of the time (3) • Most of the time (4) • Always (5)
Block 2: Establishing the control scenario for measuring perceived safety and willingness to visit the restaurant	Please read the description of a popular restaurant in your area below. You will be asked questions about this restaurant, but remembering related details is not important. *Foodalicious* is a downtown restaurant in your area that offers well-cooked and presented, moderately priced meals for singles, groups, and families. Menu items suit the taste of children and adults. The atmosphere is pleasant and informal. There is comfortable seating and table service. ***Q3***. Given your current perception of COVID-19 related risks, to what extent do you agree with the following statements: 17. I feel safe going to *Foodalicious* to eat a meal. 18. I believe that it is safe to reopen *Foodalicious.* 19. I am sure that *Foodalicious* is reliable in terms of ensuring health safety. 20. I would go to *Foodalicious* with friends or family. 21. I would like to visit *Foodalicious* in the near future.	• Strongly disagree (1) • Disagree (2) • Slightly disagree (3) • Neutral (4) • Slightly agree (5) • Agree (6) • Strongly agree (7)

<table>
<tr><th>Block</th><th>Measurement</th><th>Scale</th></tr>
<tr><td></td><td>
22. I would consider revisiting Foodalicious in the near future.
23. I would encourage others to visit Foodalicious in the near future.
</td><td></td></tr>
<tr><td>Block 3_amb: Measuring the effect of IoT ambient sensors on perceived safety and willingness to visit the restaurant</td><td>
Foodalicious has recently introduced IoT sensors that measure ambient functions (temperature, humidity, CO_2) in their restaurant.

It has been scientifically proven that humidity, temperature, and CO_2 sensors can give indications about the risk of virus spread in the air.

Q3_amb. Given your current perception of COVID-19 related risks and the information on IoT sensors given by Foodalicious, to what extent do you agree with the following statements:

24. I feel safe going to Foodalicious to eat a meal.
</td><td>
• Strongly disagree (1)
• Disagree (2)
• Slightly disagree (3)
• Neutral (4)
• Slightly agree (5)
• Agree (6)
• Strongly agree (7)
</td></tr>
</table>

Block	Measurement	Scale
	25. I believe that it is safe to reopen *Foodalicious*. 26. I am sure that *Foodalicious* is reliable in terms of ensuring health safety. 27. I would go to *Foodalicious* with friends or family. 28. I would like to visit *Foodalicious* in the near future. 29. I would consider revisiting *Foodalicious* in the near future. 30. I would encourage others to visit *Foodalicious* in the near future.	
Block 3_occ: Measuring the effect of IoT occupancy sensors on perceived safety and willingness to visit the restaurant	*Foodalicious* has also recently introduced IoT sensors that measure space occupancy in their restaurant. It has been scientifically proven that proper social distancing can reduce the spread of the coronavirus (COVID-19). IoT occupancy sensors can lead to a better social distancing of tables and people. 	• Strongly disagree (1) • Disagree (2) • Slightly disagree (3) • Neutral (4) • Slightly agree (5) • Agree (6) • Strongly agree (7)

Block	Measurement	Scale
	Q3_occ. Given your current perception of COVID-19 related risks and the information on IoT sensors given by Foodalicious, to what extent do you agree with the following statements: 31. I feel safe going to *Foodalicious* to eat a meal. 32. I believe that it is safe to reopen *Foodalicious.* 33. I am sure that *Foodalicious* is reliable in terms of ensuring health safety. 34. I would go to *Foodalicious* with friends or family. 35. I would like to visit *Foodalicious* in the near future. 36. I would consider revisiting *Foodalicious* in the near future. 37. I would encourage others to visit *Foodalicious* in the near future.	
Block 4: Demographic questions	***Q4***. What is your gender? 38. Male 39. Female 40. Non binary/third gender 41. Prefer not to say ***Q5.*** What is your age? 42. 18 - 25 43. 26 - 35 44. 36 - 45	

Block	Measurement	Scale
	45. 46 - 55 46. 56 - 75 47. Over 75 ***Q6.*** What's your highest level of education? 48. No formal education 49. High school diploma 50. College degree 51. Vocational training 52. Bachelor's degree 53. Master's degree 54. Professional degree 55. Doctorate degree 56. Other ***Q7.*** Not considering the COVID-19 pandemic, about how often do you eat at a sit-down restaurant 57. Every day 58. A few times a week 59. A few times a month 60. Less than a few times a month 61. Never ***Q8.*** Have you been infected with the Coronavirus (COVID-19)?	

Block	Measurement	Scale
	62. Yes, and I have immunity	
	63. Yes, but I don’t have immunity	
	64. No	
	Q9. Have you received your Coronavirus (COVID-19) vaccination?	
	65. Yes, I have	
	66. I am in the process of completing my vaccination	
	67. No, but I plan to	
	68. No, and I don’t plan to.	
Ending Page	Thank you for taking the time to take part in our online experiment! We truly value the information you have provided. If you have any questions about the research study, please contact the researchers, Ms. Megi Hamza (megi.hamza@student.bi.no) or Ms. Anthea Bellavista (anthea.bellavista@student.bi.no).	

11.2 *Validity and Reliability of the Chosen Scales*

All selected scales have proved acceptable levels of reliability and validity. Perceived safety, adapted from Hakim et al (2020), Ngo et al (2020) and Hakim et al (2021), has a $CR = 0.86$ and $AVE = 0.63$. Perceived risk sensitivity to COVID-19, adapted from Costa (2020) and reported by Hakim et al (2021), has $CR = 0.84$ and $AVE = 0.57$. Willingness to visit the restaurant by Ryu et al (2012) has $AVE = 0.53$, Cronbach Alpha equal to 0.84 and reliability 0.74. Perceived threat of COVID-19 explains 67.9% of variance. Reliability and validity data were not available for Information sources reported by Yang & Xin (2020).

Variable	Source	Source validity & reliability	Reported Cronbach's Alpha
Perceived safety	Hakim et al, 2021, Hakim et al., 2020, Ngo et al., 2020	CR=0.86, AVE=0.63	.902
Willingness to visit the restaurant	Ryu et al., 2012.	AVE=0.53, Cronbach's Alpha=0.84, reliability=0.74	.901
Perceived threat of COVID-19	Conway et al., 2020	Variance explained=67.9%	.754
Perceived risk sensitivity to COVID-19	Hakim et al., 2021 Costa, 2020	CR=0.84, AVE=0.57	.890
Information sources regarding COVID-19	Yang & Xin, 2020	N.A.	.835

11.3 Output from the PROCESS procedure in SPSS (version 23) for the ambient sensors, safety perceptions, and willingness to visit simple mediation analysis.

```
Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 3.5.3 ****************

      Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
   Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
   Y  : visit
   X  : ambsens
   M  : safety

Sample
Size:  787

**************************************************************************
OUTCOME VARIABLE:
 safety

Model Summary
       R      R-sq       MSE         F       df1       df2         p
    .1607     .0258    2.3294   20.8074    1.0000  785.0000     .0000

Model
           coeff        se         t         p      LLCI      ULCI
constant    4.5811     .0769   59.5790     .0000    4.4302    4.7321
ambsens      .4963     .1088    4.5615     .0000     .2827     .7099

**************************************************************************
OUTCOME VARIABLE:
 visit

Model Summary
       R      R-sq       MSE         F       df1       df2         p
    .8243     .6794     .6757  830.6962    2.0000  784.0000     .0000

Model
           coeff        se         t         p      LLCI      ULCI
constant    1.2967     .0973   13.3254     .0000    1.1057    1.4877
ambsens     -.0714     .0594   -1.2026     .2295    -.1880     .0451
safety       .7767     .0192   40.4062     .0000     .7390     .8144

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
```

visit

Model Summary

R	R-sq	MSE	F	df1	df2	p
.1084	.0117	2.0801	9.3323	1.0000	785.0000	.0023

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.8549	.0727	66.8167	.0000	4.7123	4.9975
ambsens	.3141	.1028	3.0549	.0023	.1123	.5159

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI	c_ps
.3141	.1028	3.0549	.0023	.1123	.5159	.2166

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_ps
-.0714	.0594	-1.2026	.2295	-.1880	.0451	-.0492

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
safety	.3855	.0848	.2233	.5549

Partially standardized indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
safety	.2659	.0580	.1527	.3778

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
1000

------ END MATRIX -----

11.4 Output from the PROCESS procedure in SPSS (version 23) for the occupancy sensors, safety perceptions, and willingness to visit simple mediation analysis.

```
Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 3.5.3 ****************

      Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
   Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
   Y  : Visit
   X  : ocsensor
   M  : Safety

Sample
Size:  786

**************************************************************************
OUTCOME VARIABLE:
 Safety

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1973      .0389     2.2392    31.7594     1.0000   784.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.5811      .0754    60.7683      .0000     4.4331     4.7291
ocsensor      .6016      .1067     5.6355      .0000      .3920      .8111

**************************************************************************
OUTCOME VARIABLE:
 Visit

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .8250      .6806      .6564   834.2083     2.0000   783.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.2811      .0975    13.1347      .0000     1.0897     1.4726
ocsensor     -.0997      .0590    -1.6913      .0912     -.2154      .0160
Safety        .7801      .0193    40.3426      .0000      .7422      .8181

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
```

Visit

Model Summary

R	R-sq	MSE	F	df1	df2	p
.1292	.0167	2.0183	13.2991	1.0000	784.0000	.0003

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.8549	.0716	67.8325	.0000	4.7144	4.9954
ocsensor	.3696	.1013	3.6468	.0003	.1706	.5685

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI	c_ps
.3696	.1013	3.6468	.0003	.1706	.5685	.2581

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_ps
-.0997	.0590	-1.6913	.0912	-.2154	.0160	-.0696

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
Safety	.4693	.0847	.3045	.6335

Partially standardized indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
Safety	.3278	.0583	.2134	.4409

*********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:
95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

------ END MATRIX -----