# Antecedents of adoption intention for nanotech inside and outside applications

Master Thesis

Business Administration

Innovation & Entrepreneurship

Steffi Menten, s4283201

Supervisor: Dr Nanne Migchels

2nd Corrector: Prof. Bas Hillebrand

Radboud University

## Abstract

The current study examines adoption intention of nanotechnology applications, distinguishing between outside (food packaging) and inside (food processing) applications. The adoption of nanofoods has been widely researched, yet studies focused on either the differences in adoption for outside and inside applications or testing models for adoption in general. The aim of the current study is to combine these two types of knowledge by testing separate models for the inside and outside applications. The current study uses a confirmatory approach, providing insights into the antecedents of and mechanism behind the adoption intention for nanofoods. The research approach consisted of the distribution of two separate surveys on inside and outside applications. The results were analysed via structural equation modelling (SEM). Results clarified that adoption intention of outside applications is higher than inside applications, although in general higher than expected. In addition, the outcomes provided insights into the different antecedents for adoption for the inside (e.g. risk, naturalness) and outside (e.g. perceived benefit, trustworthiness) applications. A limitation was that generalisability was not optimal due overrepresentation of certain groups. The study is original in applying Rogers' (2003) Adoption Theory as a theoretical lens for the joint validation of two models for inside and outside applications, focusing on their differing antecedents.

## Introduction

Nanotechnology has the potential to revolutionise the food industry (Kour et al., 2015; Priestly, Harford & Sim, 2007). It can be classified as a radical innovation, based on the dimensions that it involves a new technology and provides a major possibility to fulfil customer needs (Buzby, 2010; Chandy & Tellis, 1998). Nanotechnology considers the manipulation or engineering of molecules or atoms at the nanoscale (1-100nm) (Buzby, 2010). It can be applied to food processing (nano-inside), which has led to applications that improve the consistency and sensory appeal of foods, or that improve nutrient delivery (Hamad, Han, Kim & Rather, 2018; Chellaram et al., 2014). On top of that, it can be applied to food packaging (nano-outside) as well. Applications include biodegradable packaging and measures for detection of food contamination (Hamad et al., 2018; Chellaram et al., 2014).

Despite nanotechnology food applications can lead to benefits for consumers, such as increased health benefits, increased shelf life of products and protecting food from spoiling

(Hamad et al., 2018, Buzby, 2010), consumers are hesitant to try nanotechnology food applications (e.g. Siegrist, Cousin, Kastenholz & Wiek, 2007). Awareness of nanotechnology among consumers is low, both in the USA and in Europe (Tran, Yiannaka & Giannakas, 2017; Gaskell et al., 2010). Not only do consumers now choose their foods based on specific nutrients and particular health benefits (Ensaff et al., 2015), they are also hesitant to adopt new food technologies that are associated with concepts of unnatural, unknown, unsafe and/or unhealthy (Frewer et al., 2011). The non-adoption of similar new food technologies such as irradiation and genetic modification has prevented commercialization on a large scale. In order for the adoption of nanotechnology food products to succeed, the current study tries to understand the mechanics influencing adoption intention.

Rogers (2003) found adopter characteristics and perceived characteristics of the innovation to be drivers of adoption. Results on which adoption drivers are most influential on adoption intention are contradictory. Besides adopter and product characteristics proposed by Rogers (2003), other factors are found to be influential from the food domain. Perceived naturalness and perceived risk are closely related to the adoption of new (radical) food technologies (e.g. Siegrist et al., 2008). Chang, Huang, Fu and Hsu, (2017) tested a model for adoption intention of nanotech foods where both adopter and product characteristics were incorporated. Yet, the current study argues this model is not complete, and will therefore be expanded based on the literature available in the food domain.

The adoption of nanotechnology food applications has been widely researched, yet a separation within the literature can be found: part of the literature focusses on whether outside or inside applications are more likely to be adopted (e.g. Siegrist et al., 2007; Stampfli, Siegrist & Kastenholz, 2010; Giles, Kuznesof, Clark, Hubbard & Frewer, 2015), and part of the literature focusses on testing models that explain adoption of nanotech applications in general (e.g. Chang et al., 2017). The first studies found that nano-outside applications were more likely to be adopted, whereas the latter proposed and tested a model for the adoption of nanofood applications in general. The current study attempts to combine these two insights by examining the antecedents for adoption intention for inside and outside applications via two separate models. Based on findings in the adoption theory literature in general (e.g. Rogers, 2003; Flight, D'Souza & Allaway, 2011) and specified for nanotechnology food applications (e.g. Chang et al., 2017, Giles et al., 2015) the current study hypothesizes that consumer's adoption intention for nano-outside applications is both based on different antecedents and higher compared to nano-inside applications. It builds upon the model proposed by Chang et al., (2017), in a more extensive and complete form.

Although the model proposed by Chang et al. (2017) is already a large contribution to the literature on adoption of nanotech foods, the current study can expand this knowledge in several ways. First, Chang et al. (2017) examine nanotech food applications in general, while this study distinguishes between nanotech inside and outside applications, which is argued to be of major importance for the adoption of both types of product. Secondly, the current study tries to improve the model proposed by Chang et al. (2017) by replacing the constructs that were not influential with constructs that are argued to be of influence based on additional literature in the (nanotech) food context. This will lead to valuable insights into which constructs are valuable in predicting adoption intention as well as insights into which constructs are more important for adoption for either the inside or the outside applications, or both. In addition, this study can provide manufacturers with insights into consumers' decision-making processes for the adoption of nanotech applications. It can provide advices as to which features of the products to highlight and which type of consumer to target. Thus, the research question this study probes to answer is *"What are the antecedents of the differences in adoption intention for nano-inside and nano-outside food applications?"* It is expected that nano-outside applications score higher on constructs such as perceived benefit and trustworthiness, whereas nano-inside applications will probably score higher on perceived risk.

The paper proceeds as follows. In the next section, the theoretical background will discuss the topics of radical innovations, adoption of radical innovations in general and specified for food innovation, definitions of nanotechnology and adoption intention of nanotechnology applications in the food industry. Second, a conceptual model is proposed and the methods used are described. Third, the results are presented and the paper concludes with a discussion, conclusion, practical implications and limitations including directions for future research.

## Theoretical Background

The current study examines the adoption intention of nanotechnology in the food industry, comparing inside and outside applications. This will be examined via a model that is based on a study by Chang et al. (2017) which is argued to be incomplete and will therefore be supplemented based on additions found to be relevant in the food and adoption literature. The nano-aspect is not directly visible in the model; however, all the survey questions incorporate either the nano-outside or nano-inside applications. Here at the start of the theoretical background the baseline model by Chang et al. (2017) will be provided, working towards the model the current study will test.

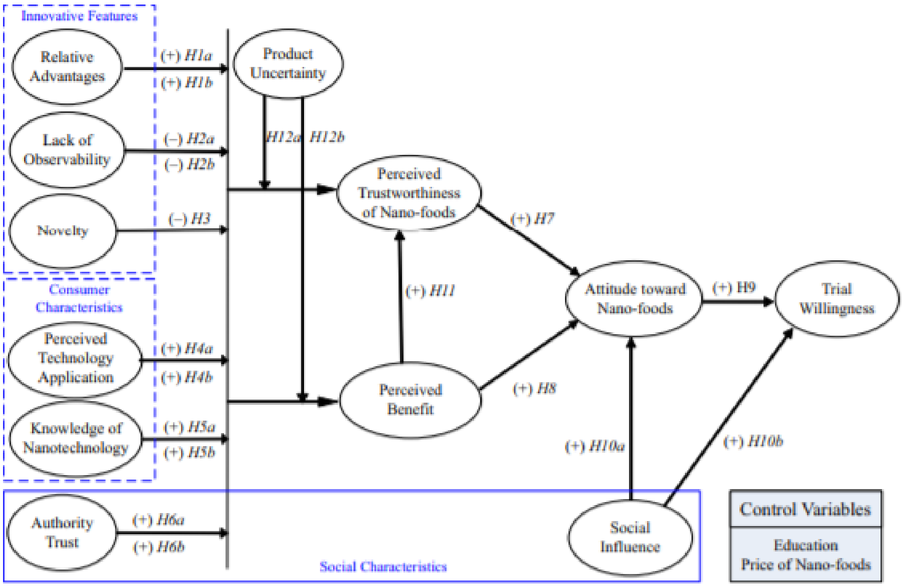


**Figure 1: Baseline model Chang et al. (2017)**

## Radical Innovations

Nanotechnology is a new form of technology and is able to fulfil new consumer needs (Chandy & Tellis, 1998). Thus, nanotechnology inside or outside food applications are a radical innovation (Buzby, 2010). A characteristic of radical innovations is that they come with risks and uncertainty. Sorescu et al. (2003) identify uncertainty at the development and introduction stage. At the development stage, there is uncertainty whether the new technology will actually lead towards ready-for-market innovations. These can be found for applications of nanotechnology that exist and are expected to be promising, but are yet unproven research ideas (Buzby, 2010). These include applications such as coated films with improved barrier properties for improved food packaging, which are still in the development stage, and the application of finite elements to food, agricultural, environmental, and biological systems, which is still a basic research idea (www.nanotechproject.org). Subsequently, at the introduction stage, uncertainty is associated with the extent and time frame of consumers' adoption of the product. Various studies address the concerns on successful consumer adoption of nanotechnology food application (e.g. Buzby, 2010; Gupta et al. 2013; Siegrist et al. 2007; Siegrist et al. 2008; Tran et al. 2017; Gaskell et al. 2010; Giles et al. 2015).

## Adoption of radical innovations

In the literature, different theoretical models are available that try to explain consumer innovation adoption, such as Rogers' (2003) Adoption Theory and the Technology Acceptance Model (TAM) (Davis, 1989). Rogers' Adoption Theory is argued to be more extensive as it consists of constructs that are comparable to the TAM in the first place, such as perceived complexity (Rogers) being represented by ease of use (Davis). Secondly, Davis (1989) focusses solely on perceived innovation characteristics, whereas Rogers' (2003) theory incorporates perceived innovation characteristics together with adopter characteristics, which are both of importance when examining adoption in the food domain. Furthermore, Davis' (1989) TAM is used especially in the information systems field. Hence, based on these differences Rogers' (2003) model is found to serve as a suitable starting point for the theoretical background.

Although Rogers' (2003) Adoption Theory consists of a process model – where consumers go through a process of consecutive stages from first awareness to possible continued use of the innovation – the current study focusses on the decision stage solely, as consumers are hesitant to even try nanotechnology food applications (e.g. Chang et al., 2017; Yue, Zhao, Cummings & Kuzma, 2015) This corresponds to Arts, Frambach and Bijmolt's (2011) division between adoption intention and actual adoption behaviour, due consumers may weigh attributes differently for purchase intention compared to purchase behaviour. Hence, adoption intention refers to the consumer's expressed desire to buy the innovation, whereas adoption behaviour refers to the (trial) purchase of an innovation.

Rogers' (2003) adoption theory has been researched extensively throughout the years, resulting in several proposed adaptations. In the first place, it has been indicated that Rogers' model is not complete. For example, Ostlund (as cited in Flight, D'Souza & Allaway, 2011) added a dimension, perceived risk, that could be of major importance on the adoption of nanotech applications. Furthermore, results are contradictory on which perceived innovation characteristics are considered to be the most important drivers of adoption intention. Plouffe et al. (2001) found relative advantage, compatibility, voluntariness and image to be important drivers of consumer adoption. These four constructs are defined as follows: *Relative Advantage* is the degree to which an individual perceives new applications to be superior to different applications (Rogers, 2003; Chang et al., 2017); *Compatibility* is the degree to which an individual believes that new applications are well-suited to his/her needs and lifestyle (Rogers, 2003; Rijsdijk et al., 2007); Voluntariness is the extent to which the adoption of an innovation is perceived to be under an individual's volitional control (Plouffe et al., 2001); and image is the degree to which an individual believes that an innovation will bestow them with added prestige or status in their relevant community (Plouffe et al., 2001). Arts et al. (2011) on the other hand, found uncertainty/perceived risk to be the most influential factor on adoption intention, showing a negative effect. *Perceived Risk* is defined as the degree to which users cannot accurately expect or predict the future effects of consuming new applications (Chang et al., 2017). In addition, compatibility, relative advantage, complexity (against expectations) and trialability showed a significant positive effect on adoption intention. A summarization of these findings can be found in a model proposed and tested by Flight et al. (2011), in which relative advantage and compatibility had a positive influence on adoption intention, whereas perceived risk had a negative influence on adoption intention. Additionally, they proposed an information construct that covered trialability, observability and communicability. This construct indirectly influenced adoption intention via relative advantage and compatibility.

Results on which adoption drivers' categories are most influential on consumer adoption are contradicting as well. Socio-demographics are found to have no effect or weak effects on both adoption intention and behaviour (Arts et al., 2011; Plouffe et al., 2001). In addition, Arts et al. (2011) find that adopter psychographics explain a relatively large percentage of variance of respectively adoption intention and adoption behaviour. Adopter psychographics that could be suitable for explaining food innovation adoption are proneness to information seeking and a consumer's level of innovativeness. *Proneness to Information Seeking* is defined as the degree to which a consumer is interested in knowing about various products and brands mainly out of curiosity (Raju, 1980), whereas *Consumer Innovativeness* is defined as the degree to which a consumer is eager to buy or know about new products or services (Raju, 1980). Proneness to information seeking, first, as this might increase consumer's awareness of radical innovations, which might in turn lead to recognition of benefits and a better understanding of risks considering the new technology. Consumer innovativeness, second, as this reflects the general disposition of a consumer to adopt a new product. Higher levels of consumer innovativeness might lead to an increase in adoption intention despite possible perceived risks.

Overall, both perceived innovation characteristics and adopter psychographics are of possible influence on adoption intention in the food domain. As results from the previously described studies originate from different domains, however, not all indicators are considered relevant for the adoption intention of food specific innovations. For instance, observability, from Rogers' (2003) original model, would probably not be an influential factor for nanotech food applications as observability is probably only an indicator for a larger construct, such as information (Flight et al., 2011). Perceived risk, relative advantage, and compatibility, on the other hand, might influence adoption intention of food nanotech applications, and are mentioned as important indicators by several studies (Plouffe et al., 2001; Flight et al., 2011). A high level of perceived risk could deter adoption intention, whereas relative advantage and compatibility could positively influence adoption intention. The same probably holds for the adopter psychographics information proneness and consumer innovativeness as explained above.

**Consumer Food Choice**

Focusing on food innovations in particular, other factors might be of influence on adoption intention as well, with regard to the different context in which the food industry operates. In order to understand how the adoption of new food technologies works it is important to first get an understanding of how consumers judge the food they buy, and how they make their food choices. Black and Campbell (2006) provide an adaptation of a model by Khan (as cited in Black & Campbell, 2006) which indicates factors that influence food choice decisions. These factors (socio-economic, educational, cultural, intrinsic, biological and physiological, personal, and family related) influence food choice decisions via the key dimensions of taste and nutrition. Although Khan (as cited in Black & Campbell, 2006) stipulated that a person selects food rather than nutrients for his/her diet, this perception might be outdated. More recent research (e.g. Ensaff et al., 2015) suggests that consumers now also choose food based on specific nutrients and their particular health benefits. In addition, Ensaff et al. (2015) mention that food taste, appearance, personal food history, habits, and familiarity are important parameters that influence consumer food choices. Barriers for choosing a particular food were for instance food neophobia and confusion around the food (on health benefits in particular). Low familiarity, food neophobia and confusion could be particularly relevant regarding food choice of nanotech food applications, as awareness of nanotechnology is low (e.g. Buzby, 2010) which can result in higher perceived risk and lower perceived benefit perceptions of consumers (e.g. Siegrist et al., 2008).

Thus, consumers' food choices are dependent on different factors than with other products. This can be explained via the "omnivore paradox" (van Trijp & van Kleef, 2008) which is defined as the tendency of humans to alternate between approaching and avoiding new food, which is grasped by the concepts of *neophilia* and *neophobia*. Neophobia could be seen reflected in an increase in perceived risk (Flight et al., 2011; Arts et al., 2011; Plouffe et al., 2001) when a consumer assesses a new food innovation considering adoption intention, as the definitions of these concepts are complementary. Neophobia can be an important concept for the adoption intention of food innovations. The majority of food product innovations fail, due consumer acceptance of food products is not well grasped (Fenko, Leufkens & van Hoof, 2015). Neophobia could be positively related to the failing of food product innovations, as food neophobia is a limitation to a consumer's readiness for trying new food products, flavours, styles and ingredients (e.g. Henriques, King & Meiselman, 2009). Tactics for overcoming or reducing neophobia towards novel food products include offering information about taste and production, and letting the consumers taste the new product (Fenko et al., 2015). Neophilia, on the other hand, could be seen reflected in high levels of consumer innovativeness as these consumers might be more daring to test new products, even in the food domain. Fenko et al. (2015) portray this tendency, as they showed that neophilics exhibit a higher intention to try and intention to buy a product that was indicated by a slogan emphasizing the newness of the product or a slogan emphasizing both the newness and familiarity of the product. No such effect was found for a slogan that emphasized the familiarity of the product. This is an important implication for the adoption of radical food innovations as these consist of novel technology and address a new customer need.

Concluding, factors that are found to be of influence on consumer food choice are neophobia, neophilia, taste, nutrition, low familiarity, confusion, offering information on taste and production, and letting consumers taste the products. These factors all revolve around the risks and benefits that come with nanotechnology as perceived by consumers.

**Adoption of other food technology innovations**

To get a better understanding of the adoption of nanotech food products, important insights into the adoption of different food technology innovations are provided here. For consumer response to new food technologies in general, Frewer et al. (2011) compared the consumer acceptance of multiple emerging food technologies. From this comparison it became clear that perceived risks and benefits were important drivers for the acceptance of all the emerging technologies. Besides, technologies that were perceived to be bioactive (that is it may impact current and future generations of humans, animals and plants) were perceived riskier. This could be linked to consumer's inappropriate risk assessment of nanotechnology (Cushen, Kerry, Cruz-Romero & Cummins, 2012). Cardello, Schutz and Lesher (2007) add to this that potential risk of the technology was the most important factor determining consumers' interest in use. Similar to Frewer et al. (2011), consumers are found to associate foods processed by novel technologies with concepts of unnatural, unknown, unsafe and/or unhealthy. Besides, Chen, Anders and An (2013) show that providing information about radically new food technologies has a positive influence on consumers' choice decisions, which is comparable to Flight et al. (2011) who found a positive indirect influence of information on adoption intention for radical innovations.

Considering specific innovative technologies in the food industry, consumer acceptance and adoption varied. First, examining the adoption intention of insect eating (entomophagy), sensory expectations and food neophobia are found to be predictors of the willingness to try edible insects, whereas past exposure negatively influenced neophobia and positively influenced sensory expectations (Sogari, Menozzi & Mora, 2018). These predictors are comparable to those found to be influential in the food choice literature (respectively taste and neophobia). House (2016) adds to this that initial motivations for trying insects included curiosity, perceived sustainability, perceived health benefits and the introduction of novelty and variety into diets. Curiosity and the introduction of novelty and variety into diets could be argued to be indicators of neophilia, being an influential factor in the food choice literature as well. Besides, the same is true for perceived health benefits. Thus, for insect eating it might be expected that adoption intention would be higher than with other new food technologies, due positive motivations for trying insects such as curiosity and perceived health benefits, and higher likely acceptance when the insects are not directly visible (Sogari et al. 2018).

Focusing on food technologies of which consumer acceptance was more difficult – which to this day prevented commercialization on a large scale of these technologies –, suitable examples are irradiation and genetic modification. DeRuiter and Dwyer (2002) argue that conservatism arises among consumers towards accepting any new food, especially with new and unfamiliar technologies such as irradiation. They find adoption to be slowed due to little knowledge about the technology. Providing consumers with information – again, matching one of the factors in food choice literature – helped the acceptance of irradiated food. Due awareness on nanotechnology being low among consumers as well, providing information might help augment the adoption intention for it. Additionally, genetically modified foods have been associated with unnaturalness, untrustworthiness, moral considerations, uncertainty, unhealthiness and risk (Chen, 2018), despite high awareness among consumers (Rollin, Kennedy & Wills, 2011). Chen (2018) adds to this that food technology neophobia influences personal domain-specific innovativeness and willingness to consume GM foods.

Overall, factors that are of importance for the adoption intention of different new food technologies match those that are found to be influential in the food choice literature. In addition, factors that are considered to be of crucial importance for the adoption of new food technologies are perceived benefits (among which health benefits), risks and naturalness as perceived by consumers (Siegrist et al., 2008).

**Nanotechnology**

Nanotechnology considers the manipulation or engineering of molecules or atoms at the nanoscale. Nanomaterials include those materials that have at least one dimension (height, length, width) at the nanoscale (1-100nm). This is comparable to a size as small as 1/80.000 of a human hair. The manipulation of nanomaterials leads familiar materials to show unique properties and behavioural traits that can be used for new applications. (Buzby, 2010). Nanomaterials in foods can occur naturally or be added intentionally. The nanoparticles that can be added intentionally are either occurring naturally in foods or not. The latter case consists of engineered material sources, which generally do not occur in foods. Lactose is an example of a naturally occurring nanoparticle, whereas nanometer salt grains (to reduce salt consumption without changing the original taste) are an example of man-made nanoparticles (Bumbudsanpharoke & Ko, 2015).

According to Singh, Jairath and Ahlawat (2016) a food application made with nanotechnology can only be classified as such when one of the following four approaches has been used during production: (1) the incorporation of nanosized or nanoencapsulated supplements and additives in a product, (2) the incorporation of nanoparticles in the packaging materials in order to improve their quality, (3) when one or more of the food's ingredients has been processed to form nanostructures (increased nutritional value or improved sensory properties of a product), and (4) When a nanotechnology based device (e.g. nanosensors) is used for the packaging or processing of a product. Based on these four approaches, two different uses of nanotechnology in the food industry can be distinguished: food processing and food packaging. Chellaram et al. (2014) define food processing as the conversion of raw ingredients into consumable food, increasing marketability and shelf life. In this process, the food quality and flavour should not change and remain as intact as possible. Besides the aim to keep foods fresh, the production of healthier foods is another important goal (Hamad, Han, Kim & Rather, 2018). Examples of nanotechnology used for food processing include improving the consistency of foods, removing toxins, improving vitamin and mineral quality and improving nutrient delivery (Hamad et al., 2018; Chellaram et al., 2014). Nanotechnology used for food processing is labelled a *nano-inside application* in the current study. The second use, food packaging, is defined as the physical protection that keeps food products safe from spoiling – due for instance external interference, temperature, and bacteria – by eliminating gasses such as oxygen (Hamad et al., 2018). Besides protecting the products, the packaging is accompanied by a label that informs the consumer about the nutritional information for the food being consumed (Chellaram et al., 2014). The applications of nanotechnology for food packaging include biodegradable packaging, plastics made from antimicrobials that have high barriers, and measures for detection of food contamination (Hamad et al., 2018; Chellaram et al., 2014). Nanotechnology applied to food packaging is labelled a *nano-outside application* in this study.

**Nanotechnology food adoption intention**

Awareness of nanotechnology among consumers is considered to be low (Tran, Yiannaka & Giannakas, 2017; Gaskell et al., 2010; Buzby, 2010). Awareness in the USA and the EU are comparable, with 70% of USA consumers reporting to know “a little” or “nothing at all” about nanotechnology (Tran et al., 2017), and 75% of EU consumers reporting they “never heard” or “only heard” about nanotechnology (Gaskell et al., 2010).

In earlier literature (e.g. Siegrist et al., 2007; Siegrist et al., 2008; Siegrist, Stampfli & Kastenholz, 2009; Stampfli et al., 2010; Giles et al., 2015), attitudes toward or acceptance of nanotechnology food applications have been discussed, mostly focusing on the distinction between nano-inside and outside applications. Siegrist et al. (2007) find that nano-inside applications are perceived as less acceptable than nano-outside applications. Trust was highlighted to be an important factor influencing this acceptance. Thus, a higher willingness to buy was expressed for nano-outside applications. However, participants were still hesitant to buy both nano-inside and nano-outside applications. Siegrist et al. (2008) focus on perceived risks and perceived benefits regarding nano-inside and nano-outside applications. Results showed that participants perceived nano-inside applications as relatively risky and nano-outside applications as less risky. Participants that perceived numerous benefits with nanotechnology food applications perceived fewer risks compared to participants that perceived fewer benefits. Thus, Siegrist et al. (2008) confirmed the findings of Siegrist et al. (2007) that nano-outside applications are considered more acceptable than nano-inside applications. These results lead to the formation of the first hypothesis, being:

*H1: Adoption intention for nanotech outside food applications is higher than for nanotech inside food applications*

In addition, Siegrist et al. (2009) focused on nano-inside applications solely, in comparison to foods with natural additives. It was found that participants would rather buy foods that provided them with health benefits that only contained natural additives compared to foods that provided them with health benefits that contained nanotechnology-based additives. Participants even preferred foods with no health benefits over foods with health benefits due nanotechnology-based additives. This shows that perceived naturalness is an important indicator for adoption intention of nanotechnology foods. *Perceived Naturalness* is defined as the degree to which an individual describes an object as being natural rather than artificial (Zhu & Meyers-Levy, 2009) This leads to the generation of the second hypothesis, being:

*H2: Perceived naturalness positively influences adoption intention for nanotech food applications*

Furthermore, results of Stampfli et al. (2010) were in line with these previous studies as well: acceptance of nanotechnology products was greatest for applications that were not to be ingested by consumers (nano-outside applications), such as UV-protection packaging, antibacterial food containers and decay-inhibiting film. Finally, a systematic review by Giles et al. (2015) that summarized these findings among others, showed that perceived benefits and risks are likely to be important determinants of consumer responses.

These influential factors are similar to the ones found for the adoption of other food technologies (perceived risks, benefits and naturalness)**.** This raises concerns for the adoption of nanotechnology food applications, as consumers are apparently hesitant to accept new food technologies that are associated with potential risks and without knowledge of any clear benefits. However, providing consumers with information on the technology might help with the acceptance, similar to the effects found for irradiation technology (DeRuiter & Dwyer, 2002). Thus, applications are more likely to be accepted if the benefits outweigh the risks. In addition, food packaging was perceived as more acceptable than nanotechnology as an integral part of food products themselves. Lastly, it was found that if nanotechnology led to cheaper and safer consumer products, this could result in increased acceptability. This leads to the development of hypothesis 3 and 4:

*H3: Perceived benefit positively influences adoption intention for nanotech food applications*

*H4: Perceived risk negatively influences adoption intention for nanotech food applications*

In more recent literature, focus shifted to examining consumer behaviours regarding nanotech food products in general. Chang et al. (2017) integrated innovation, consumer characteristics and social characteristics from Rogers' diffusion of innovations theory, Davis' technology acceptance model, and social capital perspectives and their influences on consumers perceptions of and attitudes towards nano-foods, together with willingness to try. Trial willingness is argued to be roughly comparable to adoption intention, the construct examined in this study. As the current study uses Rogers' adoption theory as a theoretical lens, the characteristics that were included in the study of Chang et al. (2017) from this specific theory will be elaborated on. Chang et al. (2017) included three of Rogers' perceived characteristics of the innovation: relative advantage, (lack of) observability, and novelty. However, novelty is not one of Rogers' five innovation characteristics, but rather a dimension of a radical innovation (newness of technology) as proposed by Chandy and Tellis (1998). The study's results showed that relative advantage indirectly influenced (positive) trial willingness via perceived benefit/perceived trustworthiness and attitude. Moreover, lack of observability indirectly influenced (negative) trial willingness via perceived trustworthiness and attitude. So, again, trustworthiness was found to be an influential factor on adoption intention. This leads to the development of the fifth hypothesis:

*H5: Perceived trustworthiness positively influences adoption intention for nanotech food applications*

As the other constructs proposed by Chang et al. (2017) for adopter and innovation characteristics besides relative advantage were not significant, the current study proposes different constructs that have been found to be influential in previous studies (e.g. Flight et al., 2011; Arts et al., 2011). To the author's best knowledge these have not been tested often in the food domain yet and can therefore make a contribution to existing literature. For the adopter characteristics, these are consumer innovativeness and proneness to information. For the innovation characteristics, compatibility is added to the model. This leads to the generation of hypotheses six up until nine:

*H6a: Relative advantage positively influences perceived trustworthiness for nanotech food applications*

*H6b: Relative advantage positively influences perceived benefit for nanotech food applications*

*H7a: Compatibility positively influences perceived trustworthiness for nanotech food applications*

*H7b: Compatibility positively influences perceived benefit for nanotech food applications*

*H8a: Consumer innovativeness positively influences perceived trustworthiness for nanotech food applications*

*H8b: Consumer innovativeness positively influences perceived benefit for nanotech food applications*

*H9a: Consumer proneness to information positively influences perceived trustworthiness for nanotech food applications*

*H9b: Consumer proneness to information positively influences perceived benefit for nanotech food applications*

## Conceptual model

Recalling the results from the empirical studies that tested Rogers' model (e.g. Flight et al. 2011, Arts et al., 2011) the perceived adopter characteristics both influential and applicable to adoption of nanotech food applications are proneness to information and consumer innovativeness. For the perceived innovation characteristics, perceived risk, relative advantage and compatibility show significant influence. Shifting focus towards the food domain, the influential constructs such as neophobia, neophilia, taste, nutrition, low familiarity, confusion, and information all relate to the perceived risk and benefit perception of consumers. Furthermore, the constructs with a significant influence on consumer food choice are applicable to the adoption intention for other new food technology innovations as well. Here, again, perceived risks and benefits are stressed, and the importance of perceived naturalness is highlighted. Finally, these constructs are important for the adoption of nanotechnology food applications too, together with perceived trustworthiness (Siegrist et al., 2007). In addition, adoption intention for nanotechnology inside applications is proposed to be lower than for outside applications.

Based on the model proposed by Chang et al. (2017) the conceptual model for the current study is developed. In the original model (see Figure 1), Chang et al. (2017) examine the influence of product, adopter, and social characteristics on adoption intention via perceived trustworthiness and benefit. The product characteristics included were relative advantage, lack of observability and novelty, argued to be based on Rogers' (2003) adoption diffusion model. Relative advantage (positive) and lack of observability (negative) were argued to influence both perceived trustworthiness and benefit, whereas novelty was hypothesized to negatively influence perceived trustworthiness. Both hypotheses for relative advantage were supported, which resulted in the current study trying to replicate this relationship. In addition, an effect for lack of observability on perceived trustworthiness was found. The other effects were not significant. Furthermore, the adopter characteristics included were perceived technology application and knowledge of nanotechnology, proposed to have a positive effect on both perceived trustworthiness and perceived benefit. The only hypothesis that was supported was the effect of perceived technology application on perceived benefit. The rest of the effects were found to be nonsignificant. Third, the social characteristics were measured via authority trust and social influence, for which the effects were significant. However, it is beyond the scope of the current study to include social characteristics as well. Product uncertainty was added to the model as a moderator influencing the relationships between the product, adopter, and social characteristics and perceived benefit and trustworthiness. The results for these hypotheses were mixed, with half being supported and half not being supported. In the current study a construct comparable to product uncertainty, perceived risk, is added. However, this construct is argued to have a direct influence on adoption intention based on earlier literature (e.g. Giles et al., 2015). Perceived trustworthiness and perceived benefit were argued to influence attitude towards nano-foods, which hypotheses were both supported. The latter construct will not be replicated in the current study due the limited scope of the current study. Instead, the direct effect of trustworthiness and benefit on adoption intention will be measured. Lastly, attitude towards nano-foods was hypothesized to influence trial willingness, which was supported as well. The structure of the model is maintained, however different adopter characteristics and product characteristics are used except for relative advantage.

It is argued that the model requires adaptation as quite a lot of the proposed relations were found to be not significant. Based on the literature in the food domain the current study proposes to include different constructs. Thus, the product characteristics included are relative advantage and compatibility, whereas the adopter characteristics included are consumer innovativeness and proneness to information. Besides perceived benefit and trustworthiness, perceived risk and naturalness are added as these are factors found to be influential for adoption intention in the food literature. Age, gender and education are included as control variables. The proposed relationships are based on the model by Chang et al. (2017) who found perceived benefit and perceived trustworthiness as significant influences on adoption intention for nanotechnology food products.

For the innovation characteristics, it is hypothesized that relative advantage positively influences perceived trustworthiness and perceived benefits of nanotechnology, thus indirectly influencing adoption intention. Relative advantage has been proven to be a useful determinant in measuring adoption intention (e.g. Flight et al., 2011). In addition, it is proposed that if performance of a product is better than comparable ones, it could infer more trust from a consumer. This is based on the results that consumers are less inclined to trust a product due performance variability issues (Becerra and Korgaonkar, 2011). Furthermore, if consumers are able to perceive more advantages of a new product, they might be better at distinguishing the benefits they can obtain from adopting the new product. For the second innovation characteristic, compatibility, it is hypothesized that this positively influences both perceived trustworthiness and perceived benefits. It is argued that if a product is more compatible to the current beliefs and routines of a consumer, the consumer might feel higher levels of trust towards the new product. In that same fashion, if the product is compatible to the current beliefs and routines of a consumer, he or she might be able to better distinguish the benefits of said product.

Regarding the adopter characteristics, it is argued that consumer innovativeness positively influences both perceived trustworthiness and perceived benefits. Higher levels of trust are expected with higher levels of consumer innovativeness as these types of consumers are fond of trying out new and unknown things first, therefore perhaps exhibiting higher levels of trust in relatively new and unknown products. In addition, higher levels of perceived benefit could be expected, as these innovative consumers are prone to try out these new products and might therefore have quite a positive attitude towards the new products. The second adopter characteristic, proneness to information, is quite comparable to the construct proposed by Chang et al. (2017) being knowledge of nanotechnology. Chang et al. (2017) argued that people will resist in using a technology if they lack technological knowledge about it. As mentioned before, consumer's knowledge of nanotechnology is limited. However, if consumers are prone to seek information about the risks and benefits of nanotechnology, this could increase both their trust levels and the benefits they perceive.

Furthermore, it is hypothesized that perceived benefits, perceived risk, perceived trustworthiness and perceived naturalness are of direct influence on adoption intention. The relations between perceived benefits and perceived trustworthiness have been proven significant by Chang et al.'s (2017) study, and will be replicated in the current one. Nanotechnology provides the possibility to improve food products' quality, which increases performance and can lead to higher trust levels with consumers. Thus, if users believe in this increase in performance provided by nanotechnology, this will lead to increased trust in the product and might therefore lead to a higher intention to adopt the product. For perceived benefit, the value for consumers can increase for food products as nanotechnology can potentially generate new food products with multiple benefits (Siegrist et al., 2008). If consumers are able to see nanofood products as more beneficial than other products this might lead to a higher adoption intention for nanofoods. Several studies in the food domain have mentioned perceived risk to be an influential factor for adoption intention (e.g. Giles et al., 2015). It is argued that an increase in perceived risks will lead to consumers being less inclined to adopt the new nanofood products. Studies before (e.g. Siegrist et al., 2007) showed that consumers are more inclined to adopt a product if the perceived benefits outweigh risks. Lastly, perceived naturalness is added as consumers tend to be scared of food products that contain unnatural ingredients (e.g. Frewer et al., 2011). Therefore, if consumers do perceive a certain level of naturalness with nanotech food products this might lead to increased levels of adoption intention as well. However, it is expected that low levels of naturalness will occur and will therefore negatively influence adoption intention. Based on this argumentation, the conceptual model used for the current study is shown in Figure 2 below.

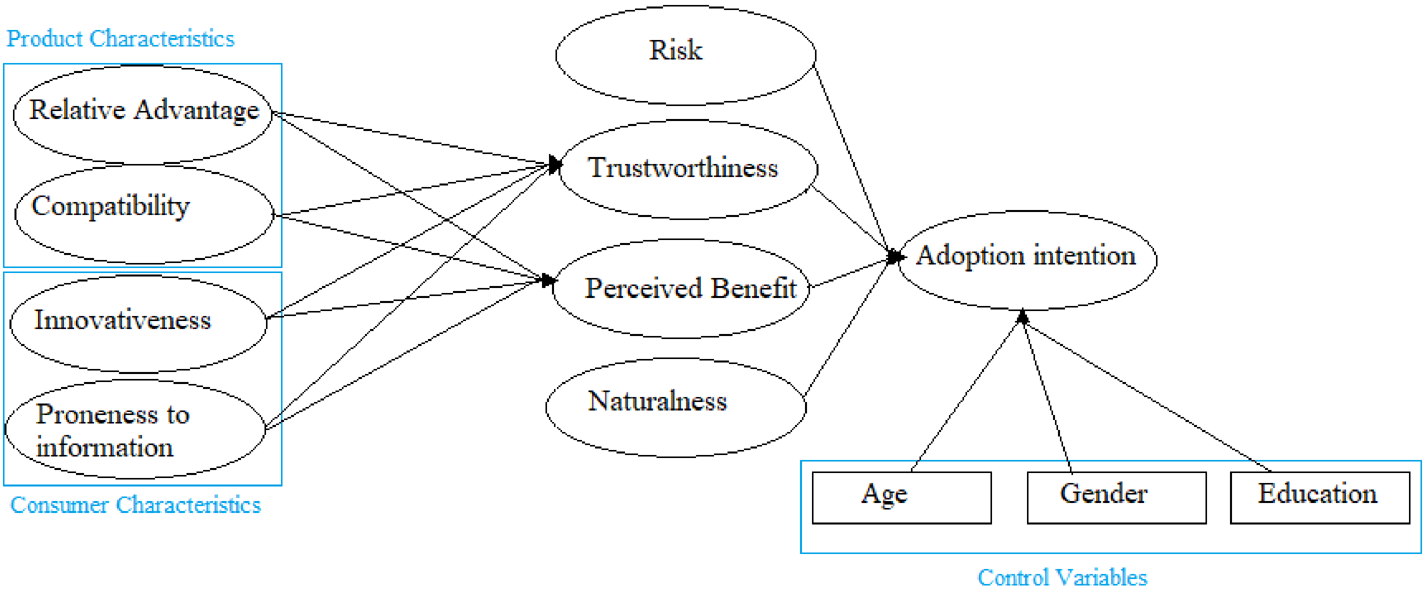


**Figure 2: Conceptual model**

# Method

## Research strategy

Existing literature on adoption intention of nanotech food applications has mainly been exploratory. Several factors have been indicated to be of influence on the adoption of nanotechnology, however some of these factors were measured via only one item (e.g. Siegrist et al., 2008), hence reducing their validity. Chang et al. (2017) tested and partly validated a more complete model. Therefore, the structure of this model is maintained. Yet, based on different studies in the food domain (e.g. Siegrist et al., 2007; Frewer et al., 2011), it is argued that there are other influential factors that should be tested relating adoption intention. In addition, the surveys from influential literature mainly cover Switzerland (Siegrist et al., 2007; Siegrist et al., 2008; Siegrist et al., 2009; Stampfli et al., 2010). Distributing a survey on nanotechnology in the Netherlands could possibly yield different results.

The present study is of confirmatory nature, as there is prior knowledge available on which factors are expected to be influential in the nanotechnology adoption context. However, these influential factors have not been examined together in one model with multiple-item measurement. Segmentation is based on the age of consumers, as they should be able to eventually buy nanotech food products if these were available. In addition, prior knowledge of nanotechnology is not required, as awareness about nanotechnology among consumers is low. Therefore, this study wants to address a population comparable to the population that could possibly be targeted for buying nanotech foods in the future. The control variables age, gender and education as well as the adopter characteristics innovativeness and proneness to information might help with segmentation afterwards in order to advise which kind of consumers to target for nanotechnology products. As awareness among consumers is expected to be low, the first part of the survey provided consumers with information on what nanotechnology is, specified for both the inside and outside applications. Whether this information was understood correctly was tested beforehand among a small sample.

As the model is quite extensive and consists of a large number of items to measure the different constructs, and testing the model is confirmatory, a quantitative research method is chosen. In order to collect such a large amount of data and to be able to address a large and varied population, distributing a survey was argued to be a suitable method. Besides, this way data gathering could transpire in a relatively short amount of time. In addition, the standardization of questions and the large and varied sample addressed adds to respectively the reliability and the generalisability of the data. Furthermore, a survey is argued to be suitable as the aim is to describe whether certain relationships between variables exist instead of trying to specify these exact relationships.

**Sample and procedure**

The population covered all consumers over eighteen years of age, with the possibility to buy their own groceries or food products, without necessarily prior knowledge about nanotechnology. In addition, in the sample consumers were not partitioned based on their food choice or dietary choices. Yet, the current study was interested in the level of consumer innovativeness and their proneness to information and whether this was related to adoption intention. The sample consisted of respondents gathered via e-mail and social media. As spreading the survey in the researcher's own network might lead to an overpopulation of young adults with a higher education, parents and other (older) relatives were targeted specifically.

The questionnaire was distributed in April and May 2019. The survey wanted to test for the adoption of applications of nanotechnology, so not per se specific products. A division was made between nano-inside and nano-outside applications. So, this way, when seen on a scale, the survey tried to tap into knowledge that is somewhere between buying into the idea versus buying an actual product. Furthermore, due a large number of items was used for measuring the variables which lead to an extensive amount of questions, two separate surveys were developed. One survey measured the factors and their influence on adoption intention of nanotech inside applications, whereas the other survey measured the influences on adoption intention of nanotech outside applications. These two surveys were compared afterwards. Regarding sample size requirements for each of the surveys, PLS is quite robust for small samples. As a rule of thumb, the 'ten times rule' was used (Hair, Hollingsworth, Randolph & Chong, 2017), indicating a minimal sample size of 40 for each survey. However, a larger sample increases the rigor to falsify the model increases, yet at the same time increasing the likelihood that the model gets rejected based on minor aspects (Henseler, Hubona & Ray, 2016). Therefore, a minimum of 80 respondents for each survey was targeted.

Data was collected from respondents through a quantitative electronic survey administrated via Qualtrics. This method, using a self-administered and a cross-sectional design, enabled collecting a large set of data in relatively little time. This was crucial due the time and cost restrictions for this study. To increase representativeness and generalisability, probabilistic sampling was used. This was achieved by distributing the survey among a large and varied as possible population, as explained above.

The survey was distributed via e-mail as well as social media. Respondents are becoming more reluctant to collaborate in surveys (Forza, 2002). To address this issue, several ways to attract and retain respondents were applied (Dillman, 1978). Respondents were informed about potential rewards in the form of gift-certificates. This was incorporated as a way to increase survey response (Fowler, 2009). Dillman, Smyth and Christian (2014) mention other ways to increase response rate: in the survey introduction, it was specified how the survey results would be useful; the name of the Radboud University was used to increase legitimacy, and; it was conveyed that others had filled out the questionnaire before.

Furthermore, to adhere to research ethics (Smith, 2003), the respondents were informed on the purpose and prospective benefits of the research, the expected duration of the questionnaire, incentives for participation and contact information. In addition, the principles from informed consent were assumed. In order to assure confidentiality, the participants were informed about the anonymous processing of their responses. This confidentiality was guaranteed since respondents were not asked to fill out any personal details except for their gender, age and education. These data could not be linked back to the persona completing the questionnaire. In addition, respondents were given the choice to skip questions if they did not feel confident in answering them. Lastly, to prevent tunnel vision from the researcher's side, perhaps focusing too much on nanotech inside and outside applications as two separate constructs, all data was analysed together as well in order to assure that these were indeed two separate concepts. Besides, the researcher tried to focus on the importance of the overall models, instead of trying to refine and reduce the model for optimal results.

**Measures and variables**

The items used to examine each construct were adjusted from previous studies to match the topic. The operational definition of each construct can be found in Appendix 1. In addition, a full overview of the operationalisation of the items is shown in Appendix 2.

*Relative Advantage* – The scale to measure relative advantage was composed of three five-point Likert scales in order to measure the degree to which consumers believe a nanotech food application is better at some function than other products. The scale was originally developed by Rijsdijk et al. (2007), based on Rogers' adoption theory. This scale consisted of three items (e.g.: 'nanotech food applications offer advantages that are not offered by competing products').

The items (for all constructs) are scored using a 5-point anchored Likert scale ranging from 'strongly disagree' (scored as '1'), 'disagree' (scored as '2'), 'neutral' (scored as '3'), agree (scored as '4') to 'strongly agree' (scored as '5').

*Compatibility* – The scale used to measure compatibility was composed of three five-point Likert scales to measure the degree to which consumers believe nanotech food applications are well-suited to his needs or lifestyle. The scale was originally developed by Rijsdijk et al. (2007), basing themselves on Rogers' adoption theory and has been tested upon its reliability and validity in past research. The scale consisted of three items. (e.g.: 'using nanotech food applications fits into my way of living').

*Consumer Innovativeness* – The items used to measure consumer innovativeness, the eagerness to buy or know about new products and services, were adapted from the Exploratory Tendencies in Consumer Behavior Scales (ETCBS) developed by Raju (1980) which possesses high face validity, low social desirability and adequate reliability. three five-point Likert scale items were used instead of the original ten items, due to cross-loadings on several constructs from the ETCBS scale and reducing the extensiveness of the number of questions. These items were checked on relevance for the current study and included or excluded on those grounds (e.g.: ‘when I see a new or different product on the shelf, I often pick it up to see what it’s like’).

*Proneness to Information* – The three five-point Likert scale items used to measure proneness to information, a consumer’s interest in knowing about various products and brands mainly out of curiosity (Raju, 1980), were adapted from the ETCBS scale as well. Three items were used instead of the original eleven, due some items cross-loading on other constructs, some not being relevant for the current study, and to guard against a too extensive questionnaire. Items included for instance ‘I often read the information on the package of products just out of curiosity’.

*Risk* – To measure perceived risk, three five-point Likert scale items were used, adapted from Chang et al. (2017) (e.g.: ‘I distrust the quality of nanotech food applications’). The items were slightly adapted; however, the original items were found to be reliable and valid.

*Naturalness* – To measure perceived naturalness three five-point Likert scale items were used, adapted from Zhu and Meyers-Levy (2009). The items were slightly adapted, where the original items found to be reliable (e.g.: ‘I perceive nanotech food applications to be natural’).

*Trustworthiness* – In order to measure perceived trustworthiness, whether consumers believe nanotech applications can meet their needs and will not harm their health, three five-point Likert scales were adapted from Chang et al. (2017) (e.g.: ‘Nanotech food applications will not bring health problems’). In the study of Chang et al. (2017) which specified on nanotech food applications as well, the items were found to be reliable.

*Perceived benefit* – To measure perceived benefit three five-point Likert scale items were used, adapted from Chang et al. (2017) (e.g.: ‘I believe that inside nanotech food applications have extra nutrition/ I believe that outside nanotech food applications can lead to less food waste’). The items were found to be reliable and valid indicators for perceived benefit.

*Adoption intention* – Three five-point Likert scale items were used to measure the adoption intention for nanotech inside and outside applications, adapted from Chang et al. (2017) (e.g.: ‘My food purchasing behaviour might be influenced by the existence of nanotech inside/outside applications’).

In the dataset, the variables relative advantage, compatibility, consumer innovativeness, proneness to information, naturalness and perceived risk were independent variables, trustworthiness and perceived benefit were both independent and dependent variables and adoption intention was a dependent variable. As control variables – which might have a possible influence on adoption intention of nanotech applications as well – age, gender and education were included. Furthermore, the variables were treated as quasi interval to simplify data analysis, even though SEM is robust for variables from ordinal level and higher.

**Analytical approach**

Structural Equation Modelling (SEM) was chosen as an analytical approach due it has the ability to model latent variables and to take into account measurement error (Henseler et al., 2016). The specific method chosen was Partial Least Squares Path Modelling (PLS) due it is a promising method particularly for new technology research and is widely used in strategic management and marketing research and beyond (Henseler et al., 2016). PLS can estimate statistical models that seek to explain dependence relationships among multiple variables. Furthermore, PLS is robust with different scale types and with non-normally distributed data.

After the required number of respondents was gathered, data was cleaned and prepared via SPSS. If the incomplete responses were deleted, the number of respondents would still be higher than the 'ten times threshold' as a rule of thumb for PLS sample size. Therefore, and based on the suspicion that these respondents had not been serious in their responses (due very short duration times), it was decided to remove the incomplete responses from the dataset. Furthermore, items NA3, CI3, PI2 and PI3 were reverse coded since these were negatively worded. Lastly, compound variables were created for AI2 and AI3 (inside) and AI1, AI2 and AI3 (outside) for Adoption Intention, and for all the other constructs including all their indicators.

Before the estimation of SEM, confirmatory factor analysis (CFA) was applied to assess the reliability and validity of the indicators for the constructs. Besides, CFA helped approximate the unobserved latent variables using the observed indicators. CFA can be applied to test the extent to which a theoretical pattern of factor loadings on prespecified constructs represent the actual data. Thus, it enables the confirmation or rejection of a preconceived theory (Hair, Black, Babin & Anderson, 2014), in this case to test whether the proposed indicators were correlated to the latent constructs.

Afterwards, SEM was applied to analyse the proposed framework. SPSS software was used to clean and analyse the dataset. ADANCO was used for SEM estimation. Since PLS can take into account measurement error, it provides the researcher with information on discriminant validity, convergent validity, indicator reliability and construct reliability for each of the measured constructs. On the basis of these outcomes, the researcher is able to form a judgement on the reliability and validity of the measurement model. If the reliability and validity of the measurement model are deemed acceptable, this indicates that the indicators are able to explain the latent constructs. In terms of reliability, these should thus be able to deliver the same values when used in different research. In terms of validity, these should thus be able to measure what they are supposed to measure. For the structural model, several goodness-of-fit measures are provided, including the standardized root mean residual (SRMR), $d_G$, and $d_{ULS}$ measures. These give the researcher insights into the reliability and validity of the structural model. However, researchers are still not always in agreement on when model fit is deemed acceptable and have different ideas on which cut-off values should be used (Henseler et al., 2016). Thus Henseler et al. (2016) advise researchers to partly rely on their own judgement as well instead of solely relying on goodness-of-fit measures. Regarding the generalisability of results, a probabilistic sampling strategy was used. However, this did not prevent from the overpopulation of younger people with a university degree that became evident. Although this implies that the results are not generalisable to the whole population, the age and education groups that were overrepresented could still provide valuable insights for the current study. Since this is one of the age groups that might actually be dealing with the adoption of nanotech food products in the future, this could be labelled one of the more important groups for this type of research.

# Results

### Descriptive statistics

Table 1 shows the descriptive statistics for both the inside and outside applications. Based on the variables Gender, Age, Education and Awareness, the inside and outside sample were comparable ($t(225) = 1.83$, $p > .05$). However, from the analysis of the descriptives it became evident that higher educated people as well as young people were overrepresented in both samples. This indicates that both samples are not comparable to the average population, which is disadvantageous for the external validity and generalisability of the study. However, young, highly educated people could be an interesting group to examine for nanotech adoption research since they might be dealing with the actual adoption of these products in the future.

**Table 1: Descriptive statistics**

| | Inside | Outside |
|---|---|---|
| Gender | Male: 42.5% | Male: 37.2% |
| | Female: 57.5% | Female: 62.0% |
| | | Other: 0.8% |
| Age | 18-25: 46.3% | <18: 2.5% |
| | 26-40: 43.3% | 18-25: 73.6% |
| | 41-60: 10.4% | 26-40: 18.2% |

| | | |
|---|---|---|
| | | 41-60: 5.0%<br>>60: 0.8% |
| Education | University: 75.4%<br>University of applied science: 18.7%<br>Community college: 3.7%<br>Secondary school: 2.2% | University: 75.2%<br>University of applied science: 16.5%<br>Community college: 1.7%<br>Secondary school: 6.6% |
| Awareness | Yes: 66.4%<br>No: 33.6% | Yes: 66.9%<br>No: 33.1% |
| Finished survey | Yes: 85.5% (118)<br>No: 14.5% (20) | Yes: 87.2% (109)<br>No: 12.8% (16) |

### Confirmatory factor analysis (CFA)

Table 2 shows the outcomes of the CFA. Since construct reliability was unacceptable for the Proneness to Information construct for both the inside and outside sample, it was decided to remove this construct from the analysis. One notable difference was that for the inside sample, indicator reliability was low for AI1 (.30), leading to unacceptable construct reliability of Adoption Intention (α = .58). After the removal of AI1 construct reliability was questionable (α >.60). For the constructs that had questionable construct reliability it was decided to retain these constructs on the basis of acceptable discriminant and convergent validity.

**Table 2: Outcomes CFA**

| | Inside | Outside |
|---|---|---|
| Construct reliability | Exceptional (α >.90): Compatibility<br>Good (α >.80): Risk, Naturalness<br>Acceptable (α >.70): Perceived Benefit<br>Questionable (α >.60): Trustworthiness, Relative Advantage, Adoption Intention, Innovativeness | Good (α >.80): Risk, Compatibility<br>Acceptable (α >.70): Naturalness, Perceived Benefit, Adoption Intention<br>Questionable (α >.60): Innovativeness, Relative Advantage, Trustworthiness<br>Unacceptable (α <.50): Proneness to Information |

| | | |
|---|---|---|
| | Unacceptable (α <.50): Proneness to Information | |
| Convergent validity | AVE > .50 for all constructs | AVE > .50 for all constructs |
| Discriminant validity | All constructs met the Fornell-Larcker criterion | All constructs met the Fornell-Larcker criterion |
| Indicator reliability | too low for AI1: .30 | acceptable for all indicators |

**SEM analysis**

*Baseline model*

*Measurement model*

Figure 3 shows the baseline model for the inside applications, whereas Figure 4 shows the baseline model for the outside applications. Table 3 shows the construct reliability, discriminant validity, convergent validity and indicator reliability for both the inside and outside model, which were used to assess the reliability and validity of the reflective measurement models.[1] Validity was considered good for both the inside and the outside model, since all constructs adhered to the criteria for convergent and discriminant validity. In addition, reliability was acceptable for both the inside and the outside model. There was still room for improvement for construct reliability and indicator reliability for some constructs and indicators. However, it was chosen to maintain the indicators due the confirmatory nature of the study and the acceptable overall construct reliability of the constructs to which the indicators belonged.

[1] For an extensive overview of the results of the analyses for the baseline and extended models for the inside and outside applications, Appendices 3 up until 6 can be consulted.

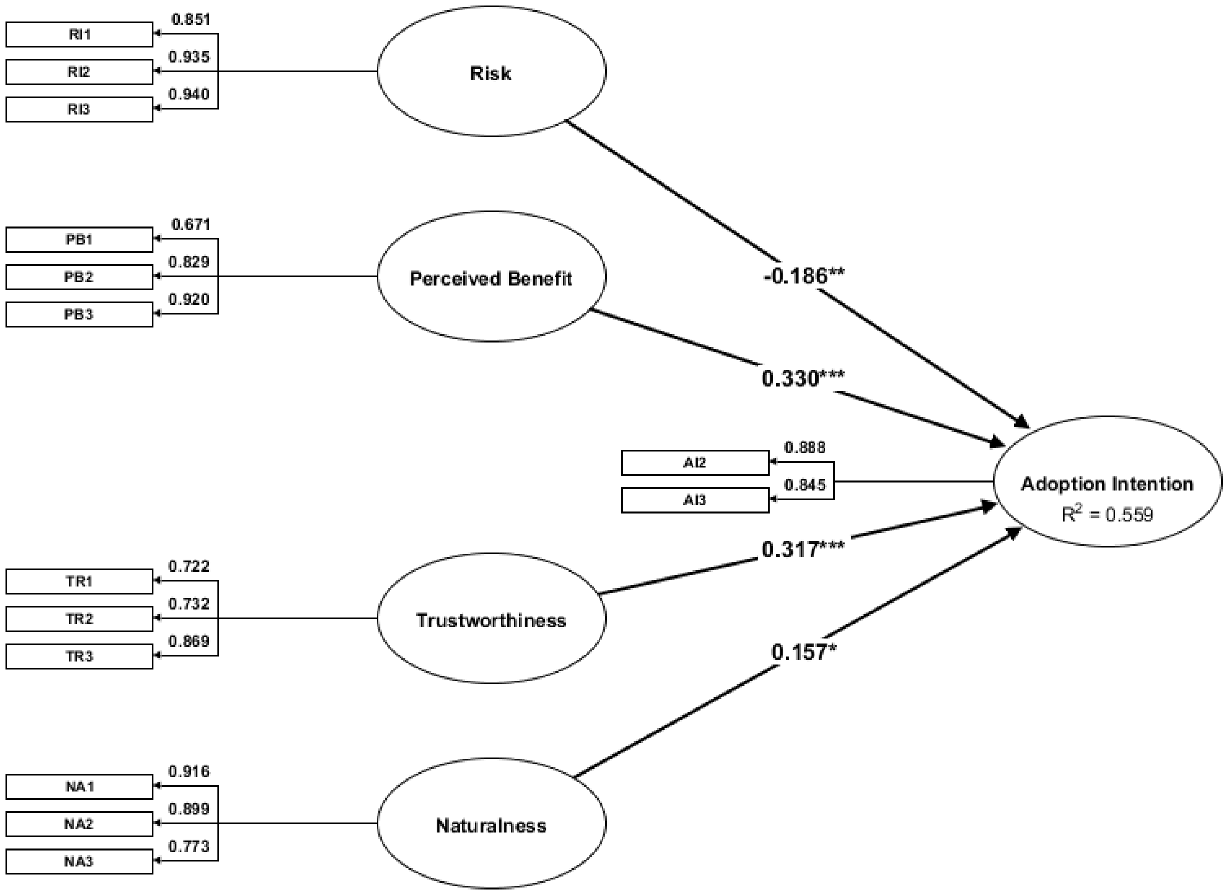


**Figure 3: baseline model inside**

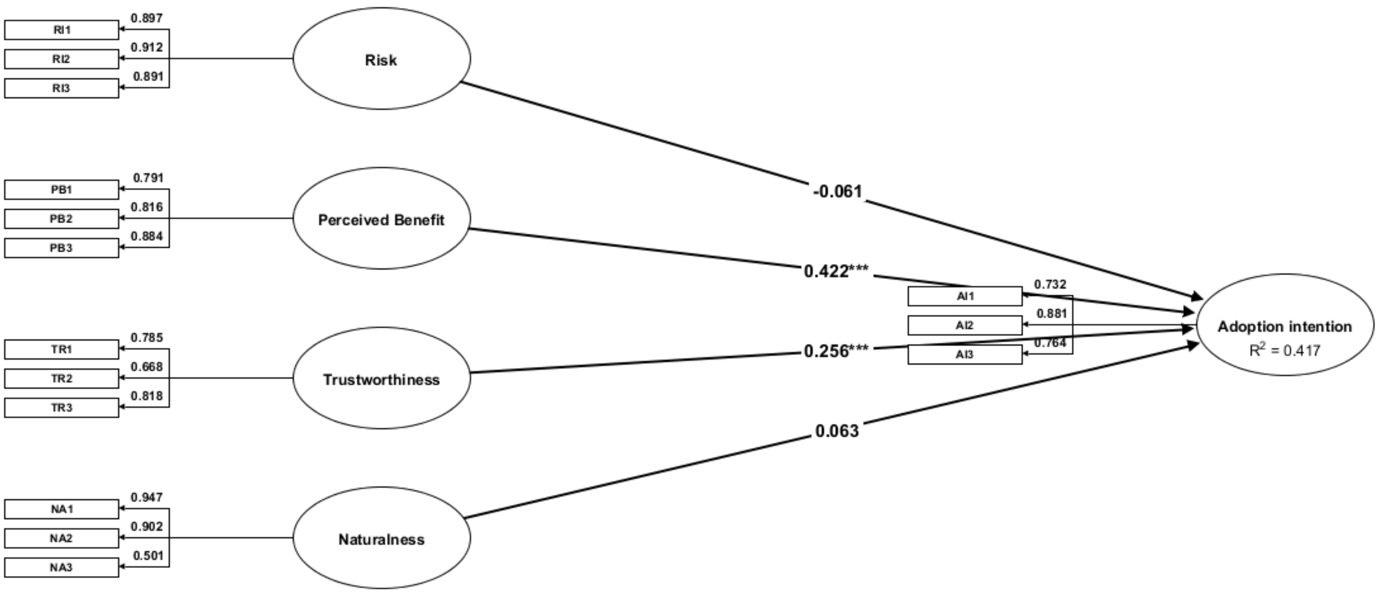


**Figure 4: baseline model outside**

**Table 3: Measurement model (baseline)**

| | Inside | Outside |
|---|---|---|
| Construct reliability | Good: Risk (α = .89), Naturalness (α = .82) Acceptable: Perceived Benefit (α = .75) Questionable: Trustworthiness (α = .69), Adoption Intention (α = .67) | Good: Risk (α = .89) Acceptable: Perceived Benefit (α = .78), Naturalness (α = .74), Adoption Intention (α = .71) Questionable: Trustworthiness (α = .65) |
| Convergent validity[2] | AVE > .50 for all constructs | AVE >.50 for all constructs |
| Discriminant validity[3] | All constructs met the Fornell-Larcker criterion | All constructs met the Fornell-Larkcer criterion |
| Indicator reliability | low for PB1 (.45), acceptable for rest of the items | low for NA3 (.25) and TR2 (.45) acceptable for the rest of the items |

*Goodness of fit*

Tables 4 up until 7 display the goodness of fit measures for the baseline model for the inside and outside applications. To assess model fit, the SRMR, $d_G$ and $d_{ULS}$ values were consulted, which quantify how strongly the empirical correlation matrix differs from the correlation matrix implied by the model (Henseler, 2017). If the values exceed the HI99 thresholds, it is unlikely that the model is true. For the outside model, it can be concluded from Table 6 and 7, that the SRMR, $d_{ULS}$ and $d_G$ values do not exceed the HI99 thresholds for both the saturated and estimated model, which indicates that the model fit is acceptable and the model is likely to be true. However, for the inside model, for which the goodness of fit measures are shown in Table 4 and 5, these led to questionable outcomes. Based on the $d_G$ values, the model would be likely to be true since these do not exceed the HI99 threshold for both the saturated and the estimated model. Yet when taking into account the SRMR and $d_{ULS}$ values, these

[2] AVE was higher than >.50 for all constructs, in both the baseline and extended models for the inside and outside applications. Hence, these will no longer be displayed in the tables for the measurement model from now on.

[3] To measure discriminant validity, the Fornell-Larcker criterion was used, which implicates that the constructs AVE is higher than its squared correlations with all other factors in the model (Henseler et al., 2016). The Fornell-Larcker criterion was met for all constructs, in both the baseline and extended models for the inside and outside applications. Hence, these will no longer be displayed in the tables for the measurement model from now on.

exceed the HI99 threshold for both the saturated and estimated model. Thus, the model fit is not optimal, but taking into account the acceptable reliability and validity of the measurement model and the acceptable $d_G$ values it is still decided that the model fit is acceptable but that there is definitely room for improvement in future research. This is not in the scope of the current study, since this study is mainly confirmatory.

**Table 4: Goodness of model fit (saturated model) (inside baseline)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.0968 | 0.0741 | 0.0882 |
| $d_{ULS}$ | 0.9846 | 0.5770 | 0.8167 |
| $d_G$ | 0.3847 | 0.3810 | 0.4875 |

**Table 5: Goodness of model fit (estimated model) (inside baseline)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.0968 | 0.0741 | 0.0882 |
| $d_{ULS}$ | 0.9846 | 0.5770 | 0.8167 |
| $d_G$ | 0.3847 | 0.3810 | 0.4875 |

**Table 6: Goodness of model fit (saturated model) (outside baseline)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.1082 | 0.1242 | 0.1403 |
| $d_{ULS}$ | 1.4050 | 1.8525 | 2.3635 |
| $d_G$ | 0.5034 | 0.7669 | 0.8882 |

**Table 7: Goodness of model fit (estimated model (outside baseline)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.1082 | 0.1242 | 0.1403 |
| $d_{ULS}$ | 1.4050 | 1.8525 | 2.3635 |
| $d_G$ | 0.5034 | 0.7669 | 0.8882 |

*Assessment of the structural model*

Table 8 shows the results for the structural model for both the inside and outside applications. The adjusted $R^2$ values for Adoption Intention for respectively the inside and the outside model were .54 and .39. This means that for the inside model, 54% of the variance in the Adoption Intention was explained by the model compared to 39% for the outside model. This difference in variance explained can be seen reflected in the number of significant relationships that were found for both models, which was higher for the inside model. Based on the outcomes in the Table, some other differences between the two baseline models become evident.

**Table 8: Results structural model (baseline)**

| | Inside | | Outside | |
|---|---|---|---|---|
| H2 Perceived Naturalness positively influences Adoption Intention for nanotech food applications | *p* <.05, β = .16, $f^2$ = .14 | Supported | *p* >.05 | Not supported |
| H3 Perceived Benefit positively influences Adoption Intention for nanotech food applications | *p* <.01, β = .33, $f^2$ = .14 | Supported | *p* <.001, β = .26, $f^2$ =.19 | Supported |
| H4 Perceived Risk negatively influences Adoption Intention for nanotech food applications | *p* <.01, β = -.19, $f^2$ = .05 | Supported | *p* >.05 | Not Supported |
| H5 Perceived Trustworthiness positively influences Adoption Intention for nanotech food applications | *p* <.01, β = .32, $f^2$ = .11 | Supported | *p* <.01, β = .26, $f^2$ = .06 | Supported |

For H2, partial support was found. Only for the inside applications a significant relationship was found between Naturalness and Adoption Intention. Naturalness positively influenced Adoption Intention, indicating that inside applications which are viewed as more natural are more likely to be adopted. However, for the outside application, no such relationship was found. A possible explanation for this outcome could be that since for outside applications consumers do not actually have to ingest it, they are less concerned with the naturalness of the product. For inside applications on the other hand, the application has to be ingested by the consumer, therefore possibly affecting their health due which they are more concerned with the product's naturalness. Thus, these outcomes are partly in line with the expectations based previous literature. Frewer et al. (2011) showed that consumers tend to be scared of food products that contain unnatural ingredients. The fact that perceived Naturalness did not influence Adoption Intention for outside applications can be explained in two ways. Either consumers are less concerned with the Naturalness of outside applications, or outside applications are perceived to be quite natural, which is the less likely explanation of the two.

For H3, full support was found, with significant effects for Perceived Benefit for both the inside and the outside applications. However, the effect was stronger for the outside applications. This indicates that Perceived Benefit is an important indicator for Adoption Intention for both nano-inside and nano-outside applications, even more so for outside than for inside applications. These results conform to the expectations formed based on previous literature. Chang et al. (2017) previously examined the influence of Perceived Benefit on Adoption Intention and found a significant positive relationship between these constructs. This relationship is thus confirmed by the current study. Siegrist et al. (2008) substantiate these results by indicating that nanotech food applications can actually lead to increased perceived benefit for consumers due the generation of new food products.

Partial support was found for H4. A significant negative effect was found for Risk on Adoption Intention for the inside applications, indicating that higher levels of perceived Risk led to a lower Adoption Intention. No such effect was found for the outside applications, which might be explained by the same reasoning as for the Naturalness construct. Since consumers do not have to ingest the outside applications, they might be less concerned with the risks accompanying the products. Giles et al. (2015) mention in their review of studies on nanotechnology food applications that perceived Risk appeared to be an influential factor on Adoption Intention. In addition, Siegrist et al. (2007) indicated that consumers are more inclined to adopt a product if the perceived benefits outweigh the risks. This is in accordance with the results found for the inside applications. However, this was not true for the outside applications. A possible reason for this might be that instead of solely examining the influence of Perceived risks and Benefits on Adoption Intention, other factors were taken into consideration as well which might have led to the incapability to identify a significant relationship. On the other hand, just as for Naturalness, it could be that consumers are less concerned with Risks accompanying outside applications.

Full support was found for H5. Significant positive relationships were found between Trustworthiness and Adoption Intention for both inside and outside applications, with weak and moderate effects respectively. Again, just as for Perceived Benefit, this indicates that Trustworthiness is an important indicator explaining Adoption Intention for nanotech food applications. These results are in line with the study conducted by Chang et al. (2017) who tested the relationship between Trustworthiness and Adoption intention as well. Besides, these results confirm the results of the study by Siegrist et al. (2007) who indicated trust to be an influential factor for the adoption of new food technologies.

*Extended model*

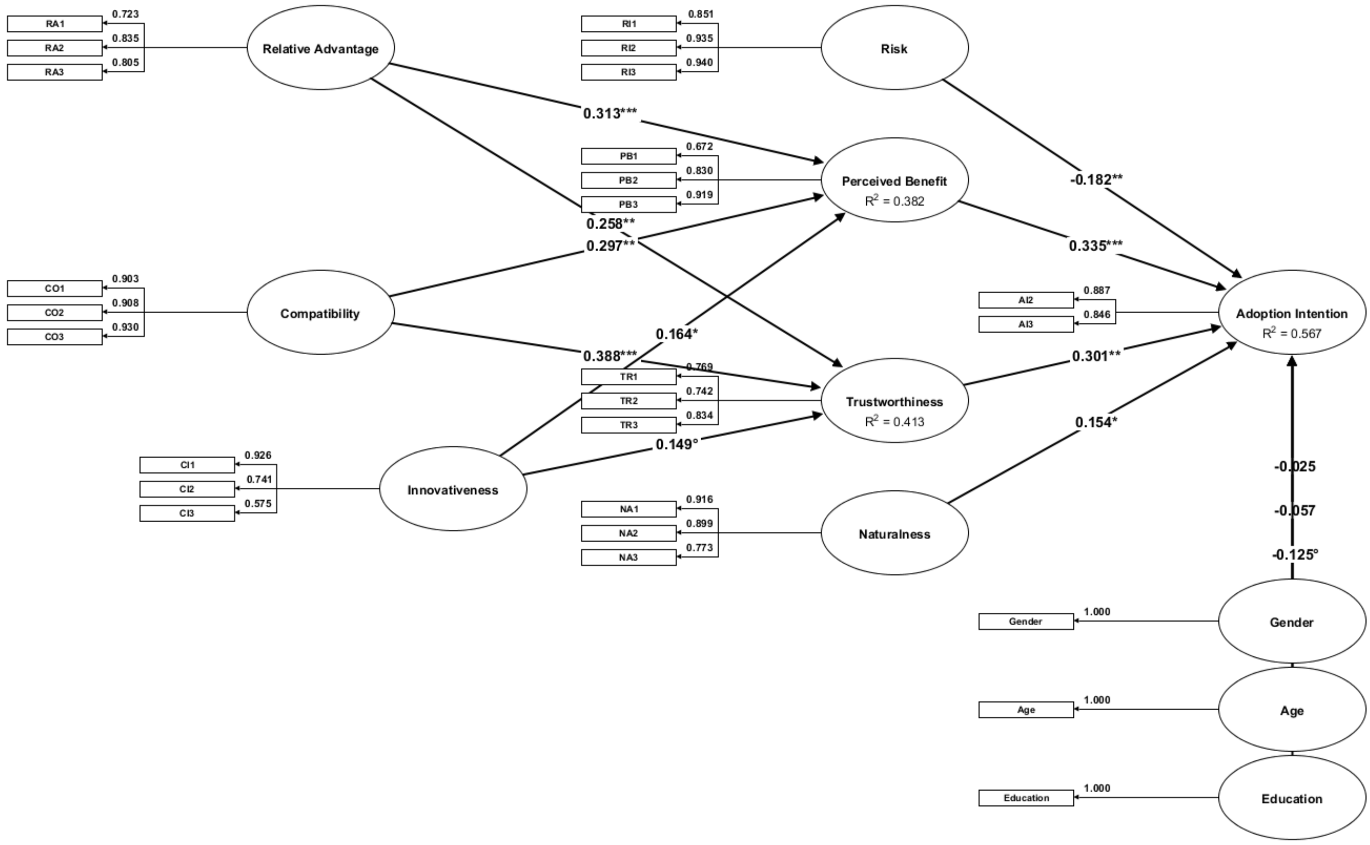


**Figure 5: extended model inside applications**

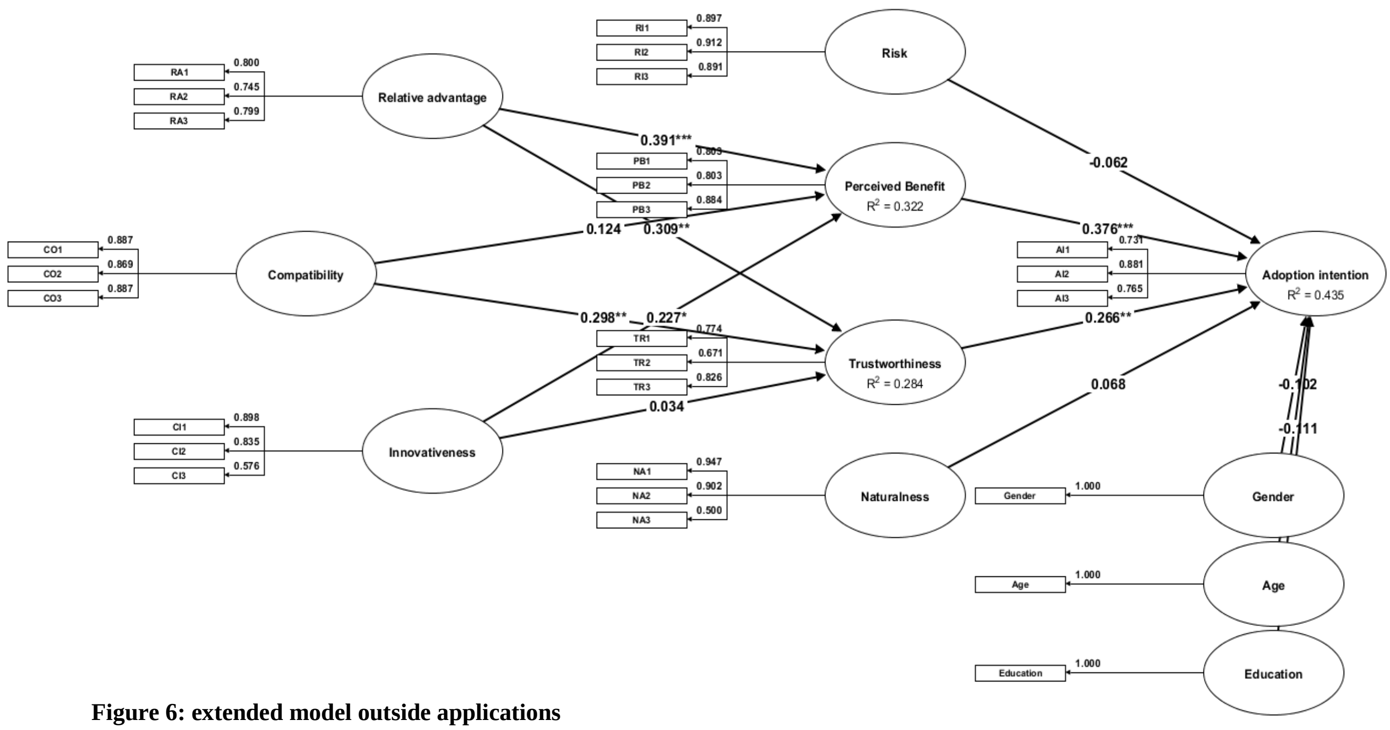


**Figure 6: extended model outside applications**

Figure 5 and 6 show the extended models for respectively the inside and the outside model. In the extended model, Relative Advantage, Compatibility and Consumer Innovativeness as well as the control variables Age, Gender and Education are included.

*Measurement model*

Table 8 displays construct reliability and indicator reliability for both the inside and outside model, which were used to assess reliability of the measurement model. As with the baseline models, the extended inside and outside models were considered valid, since convergent and discriminant validity adhered to the criteria. Overall reliability was acceptable for both models, but again, indicator reliability could be improved for a few indicators. Due the confirmatory nature of the study and the (just) acceptable construct reliability of the constructs the indicators belonged to; it was decided to retain the indicators.

**Table 9: measurement model (extended)**

| | Inside | Outside |
|---|---|---|
| Construct reliability | Exceptional: Compatibility (α = .90), Risk (α = .90)<br>Good: Naturalness (α = .83)<br>Acceptable: Perceived Benefit (α = .75)<br>Questionable: Relative Advantage (α = .69), Trustworthiness (α = .69), Innovativeness (α = .68), Adoption Intention (α = .67) | Good: Risk (α = .89), Compatibility (α = .86)<br>Acceptable: Perceived Benefit (α = .78), Naturalness (α = .74), Adoption Intention (α = .71)<br>Questionable: Innovativeness (α = .69), Relative Advantage (α = .68), Trustworthiness (α = .65). |
| Indicator reliability | low for CI3 = .33 and PB1 = .45, acceptable for the rest of the items | low for NA3 = .25, CI3 = .33, TR2 = .45, acceptable for the rest of the items |

*Goodness of fit*

Table 10 up until 13 display the goodness of fit measures for the extended models for the inside and outside applications. When comparing the goodness of fit of the two models, the outside model scores much better: it has acceptable values for all the measures for the saturated model, and an acceptable $d_G$ value for the estimated model. Based on this information the outside model cannot be rejected. The inside model displays acceptable scores for the $d_G$ measure solely. Based on this information, the inside model cannot be rejected either, but for this model there is more room for improvement regarding model fit.

**Table 10: Goodness of model fit (saturated model) (inside extended)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.0941 | 0.0660 | 0.0727 |
| $d_{ULS}$ | 3.1079 | 1.5296 | 1.8557 |
| $d_G$ | 0.9831 | 1.0151 | 1.1863 |

**Table 11: Goodness of model fit (estimated model) (inside extended)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.1044 | 0.0744 | 0.0794 |
| $d_{ULS}$ | 3.8228 | 1.9428 | 2.2105 |
| $d_G$ | 1.0932 | 1.0411 | 1.1595 |

**Table 12: Goodness of model fit (saturated model) (outside extended)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.0856 | 0.0877 | 0.0960 |
| $d_{ULS}$ | 2.7717 | 2.9066 | 3.4828 |
| $d_G$ | 1.0369 | 1.3956 | 1.6203 |

**Table 13: Goodness of model fit (estimated model) (outside extended)**

| | Value | HI95 | HI99 |
|---|---|---|---|
| SRMR | 0.1119 | 0.0921 | 0.1024 |
| $d_{ULS}$ | 4.7361 | 3.2055 | 3.9633 |
| $d_G$ | 1.2192 | 1.4352 | 1.6198 |

*Structural model*

Table 14 shows the results for the extended model for both the inside and the outside applications. The adjusted $R^2$ values were higher for the inside model (Adoption Intention: .54, Perceived Benefit: .37, Trustworthiness: .40) than for the outside model (Adoption Intention: .40, Perceived Benefit: .30, Trustworthiness: .26). This indicates that a larger amount of variance was explained by the inside model. Besides the direct effects that are displayed in Table 14, significant indirect effects were found as well. For both the inside and outside applications model, there were significant indirect positive effects for Relative

Advantage (inside: $p$ <.01, β = .18; outside: $p$ <.01, β =.23), Compatibility (inside: $p$ <.01, β = .22; outside: $p$ <.05, β =.13), and Innovativeness ($p$ <.05, β = .10; outside: $p$ <.05, β =.09) on Adoption Intention. These results confirm the influence of product and adopter characteristics on adoption (e.g. Arts et al., 2011) in this context. No significant effects were found for the control variables for the outside model. For the inside model, Education displayed a significant, negative, but weak, relationship with Adoption Intention ($p$ <.05, β = -.13, $f^2$ = .04), indicating that a higher level of completed education led to lower levels of Adoption Intention and vice versa. This in contrast to the model tested by Chang et al. (2017) where Education was included as a control variable as well, but for which no significant effect was found. This could be due the fact that a large amount of the respondents belonged to the category that finished a university degree. The results for Age and Gender were in accordance with the outcomes of Siegrist et al. (2008) who included Age and Gender as their control variables as well, and did not find a significant effect either.

Based on the outcomes of the direct effects that are displayed in Table 14, more differences between the two extended models become evident.

**Table 14: Results structural model (extended)**

| | Inside | | Outside | |
|---|---|---|---|---|
| H6a Relative advantage positively influences perceived trustworthiness for nanotech food applications | $p$ <.01, β = .26, $f^2$ = .08 | Supported | $p$ <.01, β = .30, $f^2$ = .10 | Supported |
| H6b Relative advantage positively influences perceived benefit for nanotech food applications | $p$ <.01, β = .31, $f^2$ = .11 | Supported | $p$ <.001, β = .39, $f^2$ = .17 | Supported |
| H7a Compatibility positively influences perceived trustworthiness for nanotech food applications | $p$ <.001, β = .39, $f^2$ = .17 | Supported | $p$ <.01, β = .30, $f^2$ = .09 | Supported |
| H7b Compatibility positively influences perceived benefit for nanotech food applications | $p$ <.01, β =.30, $f^2$ =.10 | Supported | $p$ >.05 | Not supported |
| H8a Consumer innovativeness positively influences perceived trustworthiness for nanotech food applications | $p$ <.05, β = .15, $f^2$ = .03 | Supported | $p$ >.05 | Not supported |

| | | | | |
|---|---|---|---|---|
| H8b Consumer innovativeness positively influences perceived benefit for nanotech food applications | $p$ <.01, β = .16, $f^2$ = .04 | Supported | $p$ <.01, β = .23, $f^2$ = .07 | Supported |
| H9a Consumer proneness to information positively influences perceived trustworthiness for nanotech food applications | - | Not supported | - | Not supported |
| H9b Consumer proneness to information positively influences perceived benefit for nanotech food applications | - | Not supported | - | Not supported |

Full support was found for H6a. Both for the inside and outside applications significant positive relationships with a weak effect were found for Relative Advantage on Trustworthiness. This indicates that higher levels of Relative Advantage result in higher levels of Trustworthiness. Full support was found for H6b as well. Significant positive effects were found for Relative Advantage on Perceived Benefit, although the effect size for the inside applications was weak, whereas the effect size for outside applications was moderate. Relative Advantage was one of the constructs that was included in the model that was tested by Chang et al. (2017). In their study, significant positive relationships were found between Relative Advantage and both Trustworthiness and Perceived Benefit. These results were replicated by the current study, for both the inside and outside applications. In addition, these results confirm that Relative Advantage is of influence on Adoption Intention, as proposed by Rogers (2003), which has already been replicated in different contexts as well (e.g. Plouffe et al., 2001; Arts et al., 2001; Flight et al., 2011).

H7a received full support as well. Significant positive relationships were found for Compatibility on Trustworthiness for both the inside and outside applications, displaying a weak effect for outside and a moderate effect for inside applications. H7b only received partial support. A significant positive and weak effect was found for Compatibility on Perceived Benefit for inside applications. However, for outside applications, no significant effect was found. Compatibility replaced two of the innovation characteristics that Chang et al. (2017) proposed in their model. This construct was expected to influence Trustworthiness and Perceived Benefit based on the structure of the model by Chang et al. (2017). In addition, it was argued that if a product is more compatible to current beliefs and routines, this might show in higher levels of trust, and, in the same way, be able to better distinguish the benefits of said product. However, this was only partly confirmed for the outside applications. No effect of Compatibility on Perceived Benefit was found. A reason for this could be that the outside applications do not necessarily need to be compatible to the consumers beliefs in order for the consumer to be able to indicate benefits related to the product. Furthermore, Compatibility was shown to be of influence on Adoption Intention in previous literature (Plouffe et al., 2001; Flight et al., 2011). This was confirmed by the current study, only the relationships were different for nanotech inside and outside applications.

Again, H8a only received partial support. For inside applications, a positive, but very weak effect, was found for Consumer Innovativeness on Trustworthiness. No such effect was found for the outside applications. H8b received full support, as for both the inside and outside applications significant positive weak effects were found for Consumer Innovativeness on Perceived Benefit. This indicates that high levels of Innovativeness result in high levels of Perceived Benefit. Consumer Innovativeness was chosen to replace one of the adopter characteristics that Chang et al. (2017) included in their model, of which none were found to be significant. This was based on the argumentation that Consumer Innovativeness reflects the general disposition of a consumer to adopt a new product. Consumer Innovativeness was expected to influence Trustworthiness as innovative consumers might have the ability to place higher trust in relatively new and unknown products. In addition, it was expected to influence Perceived Benefit as these consumers are prone to try out new products and might therefore have quite a positive attitude towards new products. Furthermore, Arts et al. (2011) found that adopter psychographics, including Consumer Innovativeness, explained a relatively large percentage of variance of Adoption Intention. This was confirmed by the current study, with different relationships for the inside and outside applications. Besides, these results confirm the findings of Fenko et al. (2015) as well, who found that people showing neophilic tendencies (comparable to Innovativeness) exhibited a higher intention to buy a product perceived as new. For outside applications Consumer Innovativeness influenced Adoption Intention via Perceived Benefit only, whereas for inside applications this was via Trustworthiness as well. This means that for outside applications the trust they had in outside applications was not determined by their innovativeness.

Both H9a and H9b received no support, since the Proneness to Information construct was deleted from both the models due low construct validity. Therefore, since these hypotheses were not tested, no further explanation of these hypotheses can be given. However, if the Proneness to Information construct were to be included in a different study the operationalisation and indicators for this construct should be refined in order to create sufficient reliability and validity.

### Model comparisons

Firstly, both models were compared based on the mean differences between the different constructs. These are shown in Table 15. From the Table, it can be concluded that H1 (*Adoption intention for nanotech outside food applications is higher than for nanotech inside food applications)* was supported, indicating that nanotechnology applied to food packaging is more likely to be adopted than nanotechnology applied to food processing. This in accordance to the expectations based on previous studies (e.g. Giles et al., 2015). However, it was surprising to see that Adoption Intention in general was more positive than expected based on previous literature, which mostly showed a negative attitude towards nanofoods (e.g. Siegrist et al., 2007). This difference in Adoption Intention partly explains why outside applications were perceived to be more compatible, trustworthy and beneficial and less risky compared to inside applications. Since inside applications are perceived as riskier, this might reflect consumers' fear towards the inside applications, which might also explain why outside applications were judged more positively. Another noteworthy finding was that no significant difference for Consumer Innovativeness was found, indicating that the samples were comparable in whether they found themselves innovative or not, which, in this case, they did. Since both samples score relatively positive on this construct this might partly explain why the attitude towards Adoption Intention is more positive than expected.

**Table 15: Comparison between inside and outside model based on separate constructs**

| Construct | Mean | | t-test |
|---|---|---|---|
| | Inside | Outside | |
| Adoption Intention | 3.07 | 3.28 | t(219.48) = -1.99, $p < .05$ |
| Risk | 3.13 | 2.63 | t(225) = 4.33, $p < .001$ |
| Perceived Benefit | 3.37 | 3.76 | t(225) = -4.26, $p < .001$ |
| Trustworthiness | 3.26 | 3.44 | t(225) = -2.26, $p < .05$ |
| Naturalness | 2.32 | 2.38 | n.s. |
| Relative Advantage | 3.40 | 3.56 | n.s. |
| Compatibility | 3.09 | 3.33 | t(225) = -2.29, $p < .05$ |
| Consumer Innovativeness | 3.44 | 3.39 | n.s. |

Secondly, the inside and outside models were compared based on the largest groups of the control variables, which were: 18-25 (Age), university degree (Education) and females (Gender). Based on education and gender, both the models displayed different relationships and significant effects on Adoption Intention, similar to the effects explained per hypothesis, indicating that the models should be used separately. When comparing the inside and outside model based on the 18-25 age group, however, the two models became more similar. The relationships for naturalness and risk were not significant anymore for the inside model, making it more comparable to the outside model. This is an interesting outcome, as this indicates that the relationships between perceived risk and naturalness on one hand and adoption intention on the other are largely explained by the age group between 26-60 for the inside model. This would imply that risk and naturalness are not as important for the young adults, indicating they might be less fearful of nanofoods in general.

In a final run, to confirm that the two models are distinguishable and should be used separately for the inside and outside applications – taken into account that the models assimilated for the 18-25 group –, all data was included in an SEM analysis. This led to unacceptable model fit, indicating that there are indeed different antecedents for Adoption Intention for inside and outside applications, for which the explanations were given with each of the different hypotheses. In addition, taken into account that the 18-25 age group was overrepresented, the discrepancy between the models would probably increase when all age groups were to be evenly represented.

## Discussion

The current study showed that there is a difference in adoption intention for nanotech inside and nanotech outside applications, the latter being more likely to be adopted. This difference has been confirmed before (e.g. Giles et al., 2015), yet the current study provided insight into where this difference originates: consumers perceive the outside applications as more compatible, trustworthy and beneficial, and less risky. In addition, adoption intention for both the inside and outside applications was higher than expected. For instance, Casolani, Greehy, Fantini, Chiodo and Mccarthy (2015) observed a cautious response to the concept of nanotechnology, similar to Giles et al. (2015) who found that consumers express concerns about nanotechnology applied to food production. The current study found that consumers' intention to adopt was somewhere between neutral and positive, indicating a positive development compared to earlier studies regarding consumers' attitudes towards nanotech food applications. This might be explained by an increase in awareness, which was found to be 66% in the current study compared to 30% in the USA (Tran et al., 2017) and 25% in the EU (Gaskell et al., 2010). Chang et al. (2017) mention that if consumers' knowledge of nanotechnology is limited, it is more difficult for them to enhance perceptions of benefits and trustworthiness. Thus, this increase in awareness might explain why consumers are more positive towards the adoption of nanotech food applications in general.

Furthermore, the antecedents for adoption intention differed as well for the inside and outside applications. Perceived benefit and trustworthiness were important indicators for adoption intention for both the inside and outside applications. Siegrist et al. (2007) proposed that high trust levels can positively influence the attitude towards nanotech products. In addition, Chang et al. (2017) found that if consumers believe nanotech foods to be trustworthy, this will result in a more positive attitude towards these products. For perceived benefit, Chen et al. (2013) showed this to be a valuable predictor of attitude towards nanotech applications. If consumers are able to perceive benefits for buying nanotech foods, they are likely to believe that these items are able to satisfy their needs which can result in more positive attitudes towards these products. For the inside applications, perceived risk and naturalness were important predictors for adoption intention as well, whereas these were not found to be influential for the outside applications. It makes sense that to consumers, these factors are more important for inside than outside applications, since consumers actually have to ingest the inside applications and might therefore be viewed as more harmful to their health. Hence, the importance of these two predictors for inside applications might be a reflection of consumers' fear towards inside nanotech applications. For the inside applications, these outcomes are in line with Frewer et al. (2011) who showed that consumers tend to be scared of food products containing unnatural ingredients. Besides, these findings therefore nuance the outcomes by Giles et al. (2015) who found risk to be influential for adoption intention, which has now been found to be influential for inside applications only.

For the innovation characteristics, both compatibility and relative advantage were important antecedents for trustworthiness, perceived benefit and, indirectly, adoption intention. Regarding relative advantage, Becerra and Korgaonkar (2011) found that the buying decisions of consumers are heavily influenced by a product's performance. Nanotech applications are able to offer extra advantages to consumers, implying enhanced performance. Since the relationship between relative advantage and perceived benefit is supported by this study, the extra advantages of nanofoods are thus able to increase the benefits perceived by consumers.

Furthermore, Chang et al. (2017) find that good product performance will result in consumers being likely to have more trust in said product. Again, results of the current study support that the extra advantages of nanofoods can increase trust of consumers in nanotech applications. For compatibility, on closer examination, these relationships were different for the inside and outside applications. It was argued that if a product is compatible to current beliefs, it is easier for consumers to see the benefits of the new product and are more likely to have trust in the new product. For the outside applications, this was not confirmed for compatibility and perceived benefit. Hence, for outside applications, perceived good product performance (relative advantage) was enough for consumers to be able to indicate the benefits that came with the product, whereas for inside applications it was important for the product to be compatible to current beliefs as well in order to be able to perceive the products benefits.

Regarding the adopter characteristics, consumer innovativeness was found to be an important precedent for trustworthiness, perceived benefit and, indirectly, adoption intention. Consumer innovativeness is the degree to which a consumer is eager to know about or try new products (Raju, 1980). This indicates a positive predisposition towards new products, which might make it easier for consumers to have trust in new products and to imagine the benefits accompanying a product. This was fully supported for the inside applications, whereas for the outside applications there was no relationship between innovativeness and trust. A possible explanation for this might be that for outside innovations trust towards these innovations was easier established, regardless of whether consumers were innovative or not. This might be related to the lower levels of fear towards the outside applications compared to the inside applications based on the unnaturalness of the inside products (Frewer et al., 2011). No relationships were found for proneness to information and respectively trustworthiness, perceived benefit and adoption intention, due unacceptable construct reliability.

Overall, the current study made valuable additions to the model proposed by Chang et al. (2017). Compatibility, consumer innovativeness, risk and naturalness are important indicators for the adoption intention of nanotech food applications, on top of the predictors that were already proposed by Chang et al. (2017), which were confirmed to be of value again. Furthermore, both adopter characteristics and product characteristics are shown to be influential factors for adoption in the context of a new food technology. This confirms the value of the theoretical lens provided by Rogers' (2003) adoption theory. Besides, the two models showed that adoption intention for nanotech inside and outside applications has different antecedents. For the inside applications part of the predictors that are important seem to be based on fear towards these applications, such as naturalness and risk, which were not important for the adoption of outside applications.

## Conclusion

The research question the current study tried to answer was *"What are the antecedents of the differences in adoption intention for nano-inside and nano-outside food applications?".* It can be concluded that adoption intention is different for outside and inside applications, both in antecedents and the willingness of consumers to adopt these applications. Consumers are more willing to adopt outside applications, although willingness to adopt is more positive than expected for both the inside and outside applications. For the inside applications, antecedents for adoption were partly based on fear towards the product, as could be seen reflected in risk and naturalness predicting adoption intention, whereas these were not influential for the outside applications. Furthermore, some minor differences were found for the influence of compatibility and consumer innovativeness on perceived benefit, trustworthiness and adoption intention, but these were less striking then the aforementioned.

Overall, the current study contributed to the insights in the adoption intention of nanofoods, and expanded the knowledge on which factors are influential for this adoption. A model proposed by Chang et al. (2017) was partly revalidated and extended with influential factors for adoption of nanotech foods. In addition, Rogers' (2003) adoption theory was proven to be a valuable theoretical lens in the context of adoption in the food industry.

Finally, regarding the commercialisation and adoption of nanotech foods in general, attitudes towards nanotech food products are more positive than expected, which is a positive development for the commercialisation of this new food technology. Therefore, it might be expected that this commercialisation, if the antecedents for adoption are taken into account, could run more smoothly, as opposed to that of different technologies in the food industry such as GM foods.

### Practical Implications

Consumers might find it difficult to observe the innovative qualities that nanofoods can bring, which might lead to a more difficult decision-making process for consumers for the adoption of nanoproducts compared to other new products. Besides, according to the current study, relative advantage and compatibility are important factors in consumer decisions on whether or not they are willing to adopt nanofood applications. Therefore, some suggestions are provided for nanotech food manufacturers.

Firstly, the current study demonstrated that better performance on behalf of nanotech products compared to different products is important to consumers in their buying decisions. Therefore, it is advised to clearly demarcate the advantage of nanotech products compared to regular products, since more consumers might be willing to try nanofoods if they know about the advantages that accompany them.

Furthermore, this study showed that consumers value products that are compatible to their current needs and lifestyle. Since consumers now base their choice of food on specific nutrients and health benefits (Ensaff et al., 2015), manufacturers should emphasize that the nanotech applications are compatible to this lifestyle, since these nanotech products are able to offer specific health benefits for consumers as well.

In addition, the current study demonstrated that consumers that are innovative might be more willing to try nanofood applications. Therefore, manufacturers should target this type of consumers at the launch of the product, since they are more likely to have a positive attitude towards the new nanofood applications.

Moreover, for the inside applications specifically, manufacturers should attempt to remove consumers' fear towards the products, based on the perceived risks and naturalness. Manufacturers could for instance cooperate with authoritative institutions – such as governmental bodies or nanotech researchers – in order to educate consumers on the risks, naturalness and benefits of nanotech products. If consumers are able to discriminate between the benefits and risk of the product and perceive it to be safe, they might be more likely to buy it.

Nanotechnology can potentially revolutionize the food industry, and is able to add value for both manufacturers and consumers. If manufacturers are able to clearly demarcate the benefits of nanofoods and inform consumers about the risks and safety concerned with the new products in a proper way, whilst targeting the right group of consumers first, adoption of nanotech foods might run more smoothly.

**Limitations and future research**

The largest part of the respondents consisted of people who finished a university degree and were between 18-25 years of age. Therefore, the generalisability of the findings might be limited to the sample examined in the current study since the respondents may not be representative enough for the general population. Future research could attempt to include a sample that is more representative for the general population, and see whether the findings of the current study would be replicated. However, due this overrepresentation it became evident that the two models assimilated when comparing them on the basis of the 18-25-year-old group. The effects of risk and naturalness for the inside model became insignificant, which might indicate that this age group is less scared of nanofoods in general compared to older people. These differences in attitudes between age groups would be an interesting distinction to further examine for future research.

Besides, nanotechnology is quite an abstract and difficult concept to explain, which might have led to some respondents not being able to fully understand the questions or what the study was about. However, around two-third of the respondents, for both the inside and outside survey, had heard of nanotechnology before, which could have been helpful for their understanding of the survey. Since a large group of consumers still has never bought or tried nanofood items before, future research could split the sample of consumers between those who have experience using nanofoods compared to those who do not have experience with nanofoods.

Furthermore, to prevent the survey from growing too extensive regarding the number of questions, the decision was made to include three indicators per construct. Still, the indicators explained the constructs quite well, which was confirmed via the CFA, except for the Proneness to Information construct which was therefore eliminated from the study. Future research could refine the measurement model by adding more indicators for the constructs with questionable reliability, in order to increase reliability and validity of the constructs itself and increase the variance explained by the model.

In addition, model fit was not perfect, but based on the measures for model fit the models could not be rejected either. Model fit was better for the outside applications, which might be due the fact that this sample was more evenly distributed. Still it was decided to not further reduce the number of constructs and indicators since this would always lead to a perfect fit ultimately. Besides, this did not adhere to the research strategy of the current study which was of confirmatory nature. For future research, different constructs could be added to the model on the basis of a different theoretical lens. This could possibly improve model fit and the variance explained by the model as well.

Moreover, the current study used Rogers' (2003) adoption theory as a theoretical lens, which could also be employed to discuss nanotechnology products in different contexts than the food industry. In addition, the proposed models could be replicated for different novel products. Besides, other theories might be applied to examine the adoption of nanofoods from another point of view.

Lastly, future research could focus on testing the model for specific nanotech food products, instead of nanotech inside and outside applications in general. This could lead to refinements of the outcomes of the current study. Then, in a later stage of nanotech product development, the preferences for specific product attributes for nanotech applications could be examined via conjoint analysis. This type of analysis could also include a comparison between nanotech food products and regular food products, and thus examine whether consumers now judge nanotech products more favourably compared to regular food products.

## References


- Arts, J.W.C., Frambach, R.T., & Bijmolt, T.H.A. (2011). Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behaviour. *International Journal of Research in Marketing, 28,* 134-144. doi: 10.1016/j.ijresmar.2010.11.002
- Becerra, E.P., Korgaonkar, P.K. (2011). Effects of trust beliefs on consumers' online intentions. *European Journal of Marketing, 45*(6), 936-962. https://doi.org/10.1108/03090561111119921
- Black, I., & Campbell, C. (2006). Food or medicine? *Journal of Food Products Marketing, 12*(3), 19-27. doi: 10.1300/J038v12n03_02
- Bumbudsanpharoke, N., & Ko, S. (2015). Nano-food packaging: An overview of market, migration research, and safety regulations. *Journal of Food Science, 80*(5). doi: 10.1111/1750-3841.12861
- Buzby, J.C. (2010). Nanotechnology for food applications: More questions than answers. *The Journal of Consumer Affairs, 44*(3), 528-545.
- Cardello, A.V., Schutz, H.G., & Lesher, L.L. (2007). Consumer perceptions of foods processed by innovative and emerging technologies: A conjoint analytic study. *Innovative Food Science and Emerging Technologies 8,* 73-83.
- Casolani, N., Greehy, G.M., Fantini, A., Chiodo, E., & McCarthy, M.B. (2015). Consumer perceptions of nanotechnology applications in Italian wine. *Italian Journal of Food Science*, *27*, 221-235.
- Chandy, R.K. & Tellis, G.J. (1998). Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *Journal of Marketing Research, 35*, 474-487
- Chang, H., Huang, C., Fu, C., Hsu, M. (2017). The effects of innovative, consumer and social characteristics on willingness to try nano-foods: Product uncertainty as a moderator. *Information Technology & People, 30*(3), 653-690. https://doi.org/10.1108/ITP-10-2015-0266
- Chellaram, C., Murugaboopathi, G., John, A.A., Sivakumar, R., Ganesan, S., Krithika, S., & Priya, G. (2014). Significance of nanotechnology in food industry. *Proceedings of the 4th International Conference on Agriculture and Animal Science, 8,* 109-113. doi: 10.1016/j.apcbee.2014.03.010

- Chen, M. (2018). Social representations of genetically modified foods and public willingness to consume such foods in Taiwan. *Journal of the Science of Food and Agriculture, 98*(14). https://doi-org.ru.idm.oclc.org/10.1002/jsfa.9086
- Chen, Q., Anders, S., & An, H. (2013). Measuring consumer resistance to a new food technology: A choice experiment in meat packaging. *Food Quality and Preference, 28*(2), 419-428. https://doi.org/10.1016/j.foodqual.2012.10.008
- Cushen, M., Kerry, J., Morris, M., Cruz-Romero, M., & Cummins, E. (2012). Nanotechnologies in the food industry – Recent developments, risks and regulation. *Trends in Food Science & Technology, 24*(1), 30-46. https://doi.org/10.1016/j.tifs.2011.10.006
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-339.
- DeRuiter, F.E., & Dwyer, J. (2002). Consumer acceptance of irradiated foods: Dawn of a new era? *Food Service Technology, 2,* 47-58.
- Dillman, D.A. (1978). *Mail and telephone surveys: The total design method.* New York (NY): Wiley.
- Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method*. Retrieved from https://ebookcentral-proquest-com.ru.idm.oclc.org
- Ensaff, H., Coan, S., Sahota, P., Braybrook, D., Akter, H., & McLeod, H. (2015). Adolescents' food choice and the place of plant-based foods. *Nutrients, 7,* 4619-4637. doi: 10.3390/nu706419
- Fenko, A., Leufkens, J., & van Hoof, J.J. (2015). New product, familiar taste: Effects of slogans on cognitive and affective responses to an unknown food product among food neophobics and neophilics. *Food Quality and Preference, 39*, 268-276. https://doi.org/10.1016/j.foodqual.2014.07.021
- Flight, R.L., D'Souza, G., & Allaway, A.W. (2011). Characteristics-based innovation adoption: scale and model validation. *Journal of Product & Brand Management, 20*(5), 343-355. https://doi.org/10.1108/10610421111157874
- Forza, C. (2002). Survey research in operations management: A process-based perspective. *International Journal of Operations & Production Management*, *22*(2), 152-194. https://doi.org/10.1108/01443570210414310

- Fowler, F.J. (2009). *Survey Research Methods ($4^{th}$ ed.).* London, United Kingdom: Sage.
- Frewer, L.J., Bergmann, K., Brennan, M., Lion, R., Meertens, R., Rowe, G., … & Vereijken, C. (2011). Consumer response to novel agri-food technologies: Implications for predicting consumer acceptance of emerging food technologies. *Trends in Food Science & Technology, 22,* 442-456. doi: 10.1016/j.tifs.2011.05.005
- Gaskell, G., Stares, S., Allansdottir, A., Allum, N., Castro, P., Esmer, Y., … Wagner, W. (2010). *Europeans and biotechnology in 2010*. Retrieved from the European Commission. doi: 10.2777/23393
- Giles, E.L., Kuznesof, S., Clark, B., Hubbard, C., & Frewer, L.J. (2015). Consumer acceptance of and willingness to pay for food nanotechnology: a systematic review. *Journal of Nanoparticle Research,* 17(12), 1-26. doi 10.1007/s11051-015-3270-4
- Gupta, N., Fischer, A.R.H., George, S., & Frewer, L.J. (2013). Expert views on societal responses to different applications of nanotechnology: A comparative analysis of experts in countries with different economic and regulatory environments. *Journal of Nanoparticle Research, 15*. doi: 10.1007/s11051-013-1838-4
- Hair, J., Hollingsworth, C.L., Randolph, A.B., & Chong, A.Y.L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442-458. https://doi.org.10.1108/IMDS-04-2016-0130
- Hamad, A.F., Han, J., Kim, B., & Rather, I.A. (2018). The intertwine of nanotechnology with the food industry. *Saudi Journal of Biological Sciences, 25,* 27-30. https://doi.org/10.1016/j.sjbs.2017.09.004
- Henriques, A.S., King, S.C., & Meiselman, H.L. (2009). Consumer segmentation based on food neophobia and its application to product development. *Food Quality and Preference, 20*(2), 83-91. https://doi.org/10.1016/j.foodqual.2008.01.003
- Henseler, J. (2017). *ADANCO 2.0.1 user manual.* Germany: Composite Modeling GmbH & Co.
- Henseler, J., Hubona, G., Ray, P.A. (2016). Using PLS path modelling in new technology research: Updated guidelines. *Industrial Management & Data Systems, 116*(1).

- House, J. (2016). Consumer acceptance of insect-based foods in the Netherlands: Academic and commercial implications. *Appetite, 107,* 47-58. http://dx.doi.org/10.1016/j.appet.2016.07.023
- Kour, H., Malik, A.A., Ahmad, N., Wani, T.A., Kaul, R.K., & Bhat, A. (2015). Nanotechnology – new lifeline for food industry. *Critical Reviews in Food Science and Nutrition.* doi: 10.1080/10408398.2013.802662
- Plouffe, C.R., Vandenbosch, M., & Hulland, J. (2001). Intermediating technologies and multi-group adoption: a comparison of consumer and merchant adoption intentions toward a new electronic payment system. *The Journal of Product Innovation Management*, *18,* 65-81.
- Priestly, B.G., Harford, A.J., & Sim, M.R. (2007). Nanotechnology: A promising new technology – But how safe? *The Medical Journal of Australia, 186*(4): 187-188.
- Raju, P.S. (1980). Optimum stimulation level: Its relationship to personality, demographics, and exploratory behaviour. *Journal of Consumer Research*, *7*, 272-282.
- Rijsdijk, S.A., Hultink, E.J. & Diamantopoulos, A. (2007). Product intelligence: its conceptualization, measurement and impact on consumer satisfaction. *Journal of the Acadamy of Marketing Science, 35*(3), 340-356.
- Rollin, F., Kennedy, J., & Wills, J. (2011). Consumers and new food technologies. *Trends in Food Science & Technology, 22*(2-3), 99-111. https://doi.org/10.1016/j.tifs.2010.09.001
- Rogers, E.M. (2003). *Diffusion of Innovations,* 5$^{th}$ edition. New York, NY: Free Press.
- Siegrist, M., Cousin, M., Kastenholz, H., & Wiek, A. (2007). Public acceptance of nanotechnology foods and food packaging: The influence of affect and trust. *Appetite, 49,* 459-466. doi: 10.1016/j.appet.2007.03.002
- Siegrist, M., Stampfli, N., Kastenholz, H., Keller, C. (2008). Perceived risks and perceived benefits of different nanotechnology foods and nanotechnology food packaging. *Appetite, 51*, 283-290. doi: 10.1016/j.appet.2008.02.020
- Siegrist, M., Stampfli, N. & Kastenholz, H. (2009). Acceptance of nanotechnology foods: a conjoint study examining consumers' willingness to buy. *British Food Journal, 111*(7), 660-668. https://doi.org/10.1108/00070700910972350
- Singh, P.K., Jairath, G., & Ahlawat, S.S. (2016). Nanotechnology: A future tool to improve quality and safety in the meat industry. *Journal of Food Science and Technology, 53*(4), 1739-1749. doi: 10.1007/s13197-015-2090-y

- Smith, D. (2003). Five principles for research ethics. *Monitor on Psychology, 34*(1).
- Sogari, G., Menozzi, D., & Mora, C. (2018). The food neophobia scale and young adults' intention to eat insect products. *International Journal of Consumer Studies, 43*, 68-76.
- Sorescu, A.B., Chandy, R.J. & Prabhu, J.C. (2003). Sources and financial consequences of radical innovation: Insights from pharmaceuticals. *Journal of Marketing, 67*(4), 82-102.
- Stampfli, N., Siegrist, M., & Kastenholz, H. (2010). Acceptance of nanotechnology in food and food packaging: a path model analysis. *Journal of Risk Research, 13*(3), 335-347. doi: 10.1080/13669870903233303
- Tran, V., Yiannaka, A., & Giannakas, K. (2017). Market potential and economic impacts of food nanotechnology innovations. *Journal of Knowledge Economics*. doi: 10.1007/s13132-017- 0494-9
- van Trijp, H.C.M., & van Kleef, E. (2008). Newness, value and new product performance. *Trends in Food Science & Technology, 19*, 562-573. doi: 10.1016/j.tifs.2008.03.004
- Yue, C., Zhao, S., Cummings, C., & Kuzma, J. (2015). Investigating factors influencing consumer willingness to buy GM food and nano-food. *Journal of Nanoparticle Research, 17.* doi: 10.1007/s11051-015-3084-4
- Zhu, R., & Meyers-Levy, J. (2009). The influence of self-view on context effects: How display fixtures can affect product evaluations. *Journal of Marketing Research, 46,* 37-45.

# Appendices

## Appendix 1: Definitions of constructs

| Construct | Definition |
|---|---|
| **Relative advantage** | Degree to which an individual perceives nanotech food applications to be superior to different foods (Rogers, 2003; Chang et al., 2017) |
| **Compatibility** | Degree to which an individual believes that nanotech food applications are well-suited to his/her needs and lifestyle (Rogers, 2003; Rijsdijk et al., 2007) |
| **Innovativeness** | Degree to which a consumer is eager to buy or know about new products or services (Raju, 1980) |
| **Proneness to information** | Degree to which a consumer is interested in knowing about various products and brands mainly out of curiosity (Raju, 1980) |
| **Risk** | Degree to which users cannot accurately expect or predict the future effects of consuming nanotech food applications (Chang et al., 2017) |
| **Naturalness** | Degree to which an individual describes an object as being natural rather than artificial (Zhu and Meyers-Levy, 2009) |
| **Trustworthiness** | Degree to which an individual believes nanotech food applications will not be harmful for their health and is able to meet their needs (Chang et al., 2017) |
| **Perceived Benefit** | Degree to which the user perceives the advantages of nanotech food applications (Chang et al., 2017) |
| **Adoption Intention** | Degree to which the consumer expresses the desire to buy nanotech food applications (Flight et al., 2011). |

## Appendix 2: Items for measuring the constructs

| | |
|---|---|
| **Relative advantage** | RA1: Nanotech food applications offer advantages that are not offered by competing products |
| | RA2: Nanotech food applications are, in my eyes, superior to competing products |
| | RA3: Nanotech food applications solve a problem that I cannot solve with competing products |
| **Compatibility** | CO1: Using nanotech food applications fits into my way of living |
| | CO2: Using nanotech food applications fit the way I do things |
| | CO3: Using nanotech food applications suits me well |
| **Risk** | RI1: I distrust the quality of nanotech food applications |
| | RI2: I am afraid nanotech food applications will be unsafe for me |
| | RI3: I am afraid nanotech food applications may harm my health |
| **Naturalness** | NA1: I perceive nanotech food applications to be natural |
| | NA2: I perceive nanotech food applications to be organic |
| | NA3: I perceive nanotech food applications to be artificial |
| **Trustworthiness** | TR1: Nanotech food applications can provide the benefits it claims to offer |
| | TR2: Nanotech food applications will not bring health problems |
| | TR3: Generally, nanotech food applications make me feel satisfied |
| **Consumer Innovativeness** | CI1: I am the kind of person who would try any new product once |

| | |
|---|---|
| | CI2: When I see a new or different product on the shelf, I often pick it up just to see what it is like |
| | CI3: I am very cautious in trying new/different products |
| **Proneness to information** | PI1: I often read the information on the package of products just out of curiosity |
| | PI2: I rarely read advertisements that just seem to contain a lot of information |
| | PI3: I usually throw away mail advertisements without reading them |
| **Perceived benefit** | PB1: I believe that inside nanotech food applications have extra nutrition/I believe that outside nanotech food applications can lead to less food waste |
| | PB2: I believe that inside nanotech food applications have the advantage of helping the body absorb nutrition more easily/I believe that outside nanotech food applications can increase shelf life |
| | PB3: Generally, I believe that nanotech food applications are beneficial |
| **Adoption intention** | AI1: My food purchasing behaviour might be influenced by the existence of nanotech inside/outside applications |
| | AI2: I would willingly purchase nanotech inside/outside applications |
| | AI3: I would be willing to pay a premium for nanotech inside/outside applications |
| **Gender** | What is your gender? |
| **Age** | What is your age? |
| **Education** | What is your highest completed education? |
| **Awareness** | Have you ever read/heard anything about nanotechnology? |

## Appendix 3: ADANCO output inside baseline model

**Construct reliability**

| Construct | Dijkstra-Henseler's rho ($\rho_A$) | Jöreskog's rho ($\rho_C$) | Cronbach's alpha ($\alpha$) |
|---|---|---|---|
| Adoption Intention | 0.6810 | 0.8578 | 0.6705 |
| Risk | 0.9201 | 0.9351 | 0.8963 |
| Perceived Benefit | 0.8951 | 0.8521 | 0.7527 |
| Trustworthiness | 0.7867 | 0.8197 | 0.6918 |
| Naturalness | 0.8448 | 0.8986 | 0.8294 |

**Convergent validity**

| Construct | Average variance extracted (AVE) |
|---|---|
| Adoption Intention | 0.7512 |
| Risk | 0.8279 |
| Perceived Benefit | 0.6612 |
| Trustworthiness | 0.6043 |
| Naturalness | 0.7482 |

**Discriminant validity: Fornell-Larcker criterion** (Squared correlations, AVE in the diagonal)

| Construct | Adoption Intention | Risk | Perceived Benefit | Trustworthiness | Naturalness |
|---|---|---|---|---|---|
| Adoption Intention | 0.7512 | | | | |
| Risk | 0.2946 | 0.8279 | | | |
| Perceived Benefit | 0.3950 | 0.1967 | 0.6612 | | |
| Trustworthiness | 0.4371 | 0.3104 | 0.4434 | 0.6043 | |
| Naturalness | 0.0667 | 0.0463 | 0.0020 | 0.0215 | 0.7482 |

**Indicator reliability**

| Indicator | Adoption Intention | Risk | Perceived Benefit | Trustworthiness | Naturalness |
|---|---|---|---|---|---|
| RI1 | | 0.7245 | | | |
| RI2 | | 0.8747 | | | |

| | | | | | |
|---|---|---|---|---|---|
| RI3 | | 0.8845 | | | |
| NA1 | | | | | 0.8386 |
| NA2 | | | | | 0.8089 |
| NA3 | | | | | 0.5971 |
| TR1 | | | | 0.5209 | |
| TR2 | | | | 0.5361 | |
| TR3 | | | | 0.7558 | |
| PB1 | | | 0.4506 | | |
| PB2 | | | 0.6869 | | |
| PB3 | | | 0.8460 | | |
| AI2 | 0.7889 | | | | |
| AI3 | 0.7134 | | | | |

**Effect overview**

| Effect | Beta | Indirect effects | Total effect | Cohen's $f^2$ |
|---|---|---|---|---|
| Risk -> Adoption Intention | -0.1857 | | -0.1857 | 0.0515 |
| Perceived Benefit -> Adoption Intention | 0.3303 | | 0.3303 | 0.1368 |
| Trustworthiness -> Adoption Intention | 0.3172 | | 0.3172 | 0.1086 |
| Naturalness -> Adoption Intention | 0.1572 | | 0.1572 | 0.0529 |

**Direct effects inference**

| Effect | Original coefficient | Standard bootstrap results | | | | | Percentile bootstrap quantiles | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean value | Standard error | t-value | p-value (2-sided) | p-value (1-sided) | 0.5% | 2.5% | 97.5% | 99.5% |
| RI -> AI | -0.1857 | -0.1841 | 0.0632 | -2.9388 | 0.0034 | 0.0017 | -0.3487 | -0.3067 | -0.0626 | -0.0249 |
| PB -> AI | 0.3303 | 0.3352 | 0.0941 | 3.5106 | 0.0005 | 0.0002 | 0.0864 | 0.1475 | 0.5186 | 0.5644 |
| TR -> AI | 0.3172 | 0.3170 | 0.0803 | 3.9516 | 0.0001 | 0.0000 | 0.0665 | 0.1470 | 0.4608 | 0.4997 |
| NA -> AI | 0.1572 | 0.1567 | 0.0718 | 2.1895 | 0.0288 | 0.0144 | -0.0436 | 0.0069 | 0.2934 | 0.3411 |

## Appendix 4: ADANCO output inside extended model:

**Construct reliability**

| Construct | Dijkstra-Henseler's rho ($\rho_A$) | Jöreskog's rho ($\rho_C$) | Cronbach's alpha ($\alpha$) |
|---|---|---|---|
| Adoption Intention | 0.6797 | 0.8579 | 0.6705 |
| Risk | 0.9202 | 0.9351 | 0.8963 |
| Perceived Benefit | 0.8889 | 0.8523 | 0.7527 |
| Trustworthiness | 0.7225 | 0.8256 | 0.6918 |
| Naturalness | 0.8444 | 0.8987 | 0.8294 |
| Relative Advantage | 0.6916 | 0.8313 | 0.6940 |
| Compatibility | 0.9090 | 0.9383 | 0.9015 |
| Innovativeness | 0.9470 | 0.7994 | 0.6842 |
| Gender | 1.0000 | 1.0000 | |
| Age | 1.0000 | 1.0000 | |
| Education | 1.0000 | 1.0000 | |

**Convergent validity**

| Construct | Average variance extracted (AVE) |
|---|---|
| Adoption Intention | 0.7513 |
| Risk | 0.8279 |
| Perceived Benefit | 0.6615 |
| Trustworthiness | 0.6126 |
| Naturalness | 0.7482 |
| Relative Advantage | 0.6224 |
| Compatibility | 0.8352 |
| Innovativeness | 0.5794 |
| Gender | 1.0000 |
| Age | 1.0000 |
| Education | 1.0000 |

**Discriminant validity: Fornell-Larcker criterion** (Squared correlations, AVE in the diagonal)

| Construct | AI | RI | PB | TR | NA | RA | CO | CI | Gender | Age | Educa |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AI | 0.7513 | | | | | | | | | | |
| RI | 0.2943 | 0.8279 | | | | | | | | | |
| PB | 0.3941 | 0.1962 | 0.6615 | | | | | | | | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| TR | 0.4129 | 0.2951 | 0.4382 | 0.6126 | | | | | | | |
| NA | 0.0668 | 0.0463 | 0.0019 | 0.0165 | 0.7482 | | | | | | |
| RA | 0.2182 | 0.1159 | 0.2767 | 0.2634 | 0.0062 | 0.6224 | | | | | |
| CO | 0.3068 | 0.1635 | 0.2733 | 03345 | 0.0931 | 0.2798 | 0.8352 | | | | |
| CI | 0.1567 | 0.1436 | 0.1431 | 0.1425 | 0.0305 | 0.1145 | 0.1335 | 0.5794 | | | |
| Gender | 0.0030 | 0.0054 | 0.0040 | 0.0026 | 0.0068 | 0.0066 | 0.0010 | 0.0177 | 1.0000 | | |
| Age | 0.0097 | 0.0239 | 0.0001 | 0.0115 | 0.0016 | 0.0002 | 0.0002 | 0.0022 | 0.0175 | 1.0000 | |
| Education | 0.0201 | 0.0012 | 0.0009 | 0.0011 | 0.0088 | 0.0000 | 0.0003 | 0.0001 | 0.0024 | 0.0102 | 1.000 |

**Indicator reliability**

| Indicator | AI | RI | PB | TR | NA | RA | CO | CI | Gender | Age | Education |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Gender | | | | | | | | | 1.0000 | | |
| Age | | | | | | | | | | 1.0000 | |
| Education | | | | | | | | | | | 1.0000 |
| RA1 | | | | | | 0.5221 | | | | | |
| RA2 | | | | | | 0.6968 | | | | | |
| RA3 | | | | | | 0.6484 | | | | | |
| CO1 | | | | | | | 0.8150 | | | | |
| CO2 | | | | | | | 0.8248 | | | | |
| CO3 | | | | | | | 0.8657 | | | | |
| RI1 | | 0.7244 | | | | | | | | | |
| RI2 | | 0.8748 | | | | | | | | | |
| RI3 | | 0.8845 | | | | | | | | | |
| NA1 | | | | | 0.8383 | | | | | | |
| NA2 | | | | | 0.8085 | | | | | | |
| NA3 | | | | | 0.5979 | | | | | | |
| TR1 | | | | 0.5918 | | | | | | | |
| TR2 | | | | 0.5512 | | | | | | | |
| TR3 | | | | 0.6948 | | | | | | | |
| CI1 | | | | | | | | 0.8577 | | | |
| CI2 | | | | | | | | 0.5496 | | | |
| CI3 | | | | | | | | 0.3306 | | | |
| PB1 | | | 0.4512 | | | | | | | | |
| PB2 | | | 0.6895 | | | | | | | | |
| PB3 | | | 0.8436 | | | | | | | | |
| AI2 | 0.7867 | | | | | | | | | | |

| | |
|---|---|
| AI3 | 0.7159 |

**R-Squared**

| Construct | Coefficient of determination ($R^2$) | Adjusted $R^2$ |
|---|---|---|
| Adoption Intention | 0.5673 | 0.5397 |
| Perceived Benefit | 0.3822 | 0.3659 |
| Trustworthiness | 0.4126 | 0.3972 |

**Effect overview**

| Effect | Beta | Indirect effects | Total effect | Cohen's $f^2$ |
|---|---|---|---|---|
| RI -> AI | -0.1822 | | -0.1822 | 0.0496 |
| PB -> AI | 0.3351 | | 0.3351 | 0.1386 |
| TR -> AI | 0.3011 | | 0.3011 | 0.0975 |
| NA -> AI | 0.1543 | | 0.1543 | 0.0511 |
| RA -> AI | | 0.1827 | 0.1827 | |
| RA -> PB | 0.3135 | | 0.3135 | 0.1107 |
| RA -> TR | 0.2579 | | 0.2579 | 0.0788 |
| CO -> AI | | 0.2163 | 0.2163 | |
| CO -> PB | 0.2972 | | 0.2972 | 0.0973 |
| CO -> TR | 0.3877 | | 0.3877 | 0.1742 |
| CI -> AI | | 0.0996 | 0.0996 | |
| CI -> PB | 0.1637 | | 0.1637 | 0.0363 |
| CI -> TR | 0.1486 | | 0.1486 | 0.0315 |
| Gender -> AI | -0.0247 | | -0.0247 | 0.0013 |
| Age -> AI | -0.0568 | | -0.0568 | 0.0070 |
| Education -> AI | -0.1250 | | -0.1250 | 0.0352 |

**Total effect inference**

| Effect | Original coefficient | Standard bootstrap results | | | | | Percentile bootstrap quantiles | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean value | Standard error | t-value | p-value (2-sided) | p-value (1-sided) | 0.5% | 2.5% | 97.5% | 99.5% |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| RI -> AI | -0.1822 | -0.1821 | 0.0629 | -2.8980 | 0.0038 | 0.0019 | -0.3370 | -0.3075 | -0.0629 | -0.0133 |
| PB -> AI | -.3351 | 0.3456 | 0.0952 | 3.5218 | 0.0004 | 0.0002 | 0.0918 | 0.1538 | 0.5388 | 0.5846 |
| TR -> AI | 0.3011 | 0.2858 | 0.0943 | 3.1938 | 0.0014 | 0.007 | -0.0060 | -0.0832 | 0.4566 | 0.4893 |
| NA -> AI | 0.1543 | 0.1537 | 0.0745 | 2.0715 | 0.0386 | 0.0193 | -0.0448 | 0.0090 | 0.3017 | 0.3526 |
| RA -> AI | 0.1827 | 0.184 | 0.0576 | 3.1694 | 0.0016 | 0.0008 | 0.0499 | 0.0789 | 0.3018 | 0.3320 |
| RA -> PB | 0.3135 | 0.3133 | 0.0905 | 3.4639 | 0.0006 | 0.0003 | 0.0830 | 0.1299 | 0.4912 | 0.5226 |
| RA -> TR | 0.2579 | 0.2629 | 0.0924 | 2.7905 | 0.0054 | 0.0027 | 0.0148 | 0.0813 | 0.4300 | 0.4829 |
| CO -> AI | 0.2163 | 0.2153 | 0.0583 | 3.7110 | 0.0002 | 0.0001 | 0.0695 | 0.1073 | 0.3317 | 0.3901 |
| CO -> PB | 0.2972 | 0.2992 | 0.0923 | 3.2202 | 0.0013 | 0.0007 | 0.0766 | 0.1256 | 0.4847 | 0.5284 |
| CO -> TR | 0.3877 | 0.3891 | 0.0788 | 4.9177 | 0.0000 | 0.0000 | 0.1715 | 0.2390 | 0.5421 | 0.6003 |
| CI -> AI | 0.0996 | 0.1064 | 0.0437 | 2.2773 | 0.0230 | 0.0115 | -0.0021 | 0.0273 | 0.1995 | 0.2276 |
| CI -> PB | 0.1637 | 0.1757 | 0.0658 | 2.4887 | 0.0130 | 0.0065 | -0.0079 | 0.0432 | 0.3104 | 0.3508 |
| CI -> TR | 0.1486 | 0.1606 | 0.0818 | 1.8167 | 0.0696 | 0.0348 | -0.0479 | -0.0024 | 0.3220 | 0.3571 |
| Gender -> AI | -0.0247 | -0.0210 | 0.0661 | -0.3734 | 0.7089 | 0.3545 | -0.1892 | -0.1484 | 0.1149 | 0.1500 |
| Age -> AI | -0.0568 | -0.0628 | 0.0650 | -0.8742 | 0.3822 | 0.1911 | -0.2504 | -0.1946 | 0.0622 | 0.1065 |
| Education -> AI | -0.1250 | -0.1256 | 0.0695 | -1.7979 | 0.0725 | 0.0363 | -0.3212 | -0.2609 | 0.0054 | 0.0460 |

## Appendix 5: ADANCO output outside baseline model:

**Construct reliability**

| Construct | Dijkstra-Henseler's rho ($\rho_A$) | Jöreskog's rho ($\rho_C$) | Cronbach's alpha ($\alpha$) |
|---|---|---|---|
| Adoption Intention | 0.7619 | 0.8363 | 0.7113 |
| Risk | 0.9235 | 0.9275 | 0.8855 |
| Perceived Benefit | 0.8324 | 0.8698 | 0.7810 |
| Trustworthiness | 0.6697 | 0.8023 | 0.6450 |
| Naturalness | 0.9535 | 0.8416 | 0.7415 |

**Convergent validity**

| Construct | Average variance extracted (AVE) |
|---|---|
| Adoption Intention | 0.6316 |
| Risk | 0.8100 |
| Perceived Benefit | 0.6905 |
| Trustworthiness | 0.5765 |
| Naturalness | 0.6537 |

**Discriminant validity: Fornell-Larcker criterion** (Squared correlations, AVE in the diagonal)

| Construct | Adoption Intention | Risk | Perceived Benefit | Trustworthiness | Naturalness |
|---|---|---|---|---|---|
| Adoption Intention | 0.6316 | | | | |
| Risk | 0.1621 | 0.8100 | | | |
| Perceived Benefit | 0.3514 | 0.2053 | 0.6905 | | |
| Trustworthiness | 0.2896 | 0.2976 | 0.3313 | 0.5767 | |
| Naturalness | 0.0040 | 0.0269 | 0.0057 | 0.0077 | 0.6537 |

**Indicator reliability**

| Indicator | Adoption Intention | Risk | Perceived Benefit | Trustworthiness | Naturalness |
|---|---|---|---|---|---|
| RI1 | | 0.8039 | | | |
| RI2 | | 0.8320 | | | |
| RI3 | | 0.7941 | | | |
| NA1 | | | | | 0.8966 |

| | | | | | |
|---|---|---|---|---|---|
| NA2 | | | | | 0.8134 |
| NA3 | | | | | 0.2510 |
| TR1 | | | | 0.6155 | |
| TR2 | | | | 0.4458 | |
| TR3 | | | | 0.6689 | |
| PB1 | | | 0.6249 | | |
| PB2 | | | 0.6652 | | |
| PB3 | | | 0.7814 | | |
| AI1 | 0.5355 | | | | |
| AI2 | 0.7754 | | | | |
| AI3 | 0.5838 | | | | |

**Effect overview**

| Effect | Beta | Indirect effects | Total effect | Cohen's $f^2$ |
|---|---|---|---|---|
| Risk -> Adoption Intention | -0.0613 | | -0.0613 | 0.0042 |
| Perceived Benefit -> Adoption Intention | 0.4223 | | 0.4223 | 0.1891 |
| Trustworthiness -> Adoption Intention | 0.2562 | | 0.2562 | 0.0633 |
| Naturalness -> Adoption Intention | 0.0626 | | 0.0626 | 0.0063 |

**Direct effects inference**

| Effect | Original coefficient | Standard bootstrap results | | | | | Percentile bootstrap quantiles | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean value | Standard error | t-value | p-value (2-sided) | p-value (1-sided) | 0.5% | 2.5% | 97.5% | 99.5% |
| RI -> AI | -0.0613 | -0.0638 | 0.0807 | -0.7592 | 0.4479 | 0.2239 | -0.2626 | -0.2167 | 0.0945 | 0.1533 |
| PB -> AI | 0.4223 | 0.4200 | 0.0808 | 5.2267 | 0.0000 | 0.0000 | 0.1967 | 0.2497 | 0.5672 | 0.6073 |
| TR -> AI | 0.2562 | 0.2650 | 0.0760 | 3.3699 | 0.0008 | 0.0004 | 0.0437 | 0.1207 | 0.4173 | 0.4715 |
| NA -> AI | 0.0626 | 0.0655 | 0.0975 | 0.6419 | 0.5211 | 0.2606 | -0.2091 | -0.1356 | 0.2321 | 0.2788 |

## Appendix 6: ADANCO output outside extended model:

**Construct reliability**

| Construct | Dijkstra-Henseler's rho ($\rho_A$) | Jöreskog's rho ($\rho_C$) | Cronbach's alpha ($\alpha$) |
|---|---|---|---|
| Adoption Intention | 0.7625 | 0.8363 | 0.7113 |
| Risk | 0.9233 | 0.9275 | 0.8855 |
| Perceived Benefit | 0.8332 | 0.8698 | 0.7810 |
| Trustworthiness | 0.6696 | 0.8029 | 0.6450 |
| Naturalness | 0.9529 | 0.8415 | 0.7415 |
| Relative Advantage | 0.6823 | 0.8246 | 0.6807 |
| Compatibility | 0.8657 | 0.9122 | 0.8563 |
| Innovativeness | 0.8000 | 0.8207 | 0.6859 |
| Gender | 1.0000 | 1.0000 | |
| Age | 1.0000 | 1.0000 | |
| Education | 1.0000 | 1.0000 | |

**Convergent validity**

| Construct | Average variance extracted (AVE) |
|---|---|
| Adoption Intention | 0.6315 |
| Risk | 0.8100 |
| Perceived Benefit | 0.6905 |
| Trustworthiness | 0.5777 |
| Naturalness | 0.6536 |
| Relative Advantage | 0.6107 |
| Compatibility | 0.7759 |
| Innovativeness | 0.6118 |
| Gender | 1.0000 |
| Age | 1.0000 |
| Education | 1.0000 |

**Discriminant validity: Fornell-Larcker criterion** (Squared correlations, AVE in the diagonal)

| Construct | AI | RI | PB | TR | NA | RA | CO | CI | Gender | Age | Educa |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AI | 0.6315 | | | | | | | | | | |
| RI | 0.1632 | 0.8100 | | | | | | | | | |
| PB | 0.3504 | 0.2021 | 0.6905 | | | | | | | | |
| TR | 0.2888 | 0.2991 | 0.3335 | 0.5777 | | | | | | | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| NA | 0.0040 | 0.0270 | 0.0053 | 0.0084 | 0.6536 | | | | | | |
| RA | 0.2001 | 0.0307 | 0.2577 | 0.2130 | 0.0065 | 0.6107 | | | | | |
| CO | 0.2100 | 0.0495 | 0.1279 | 0.2060 | 0.0055 | 0.2333 | 0.7759 | | | | |
| CI | 0.2132 | 0.0850 | 0.1214 | 0.0285 | 0.0132 | 0.0619 | 0.0382 | 0.6118 | | | |
| Gender | 0.0168 | 0.0002 | 0.0080 | 0.0001 | 0.0040 | 0.0082 | 0.0088 | 0.0086 | 1.0000 | | |
| Age | 0.0609 | 0.0167 | 0.0799 | 0.0197 | 0.0063 | 0.0257 | 0.0132 | 0.1030 | 0.0072 | 1.0000 | |
| Education | 0.0009 | 0.0042 | 0.0056 | 0.0210 | 0.0206 | 0.0092 | 0.0025 | 0.0139 | 0.0442 | 0.0085 | 1.000 |

**Indicator reliability**

| Indicator | AI | RI | PB | TR | NA | RA | CO | CI | Gender | Age | Education |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Gender | | | | | | | | | 1.0000 | | |
| Age | | | | | | | | | | 1.0000 | |
| Education | | | | | | | | | | | 1.0000 |
| RA1 | | | | | | 0.6395 | | | | | |
| RA2 | | | | | | 0.5549 | | | | | |
| RA3 | | | | | | 0.6378 | | | | | |
| CO1 | | | | | | | 0.7861 | | | | |
| CO2 | | | | | | | 0.7549 | | | | |
| CO3 | | | | | | | 0.7866 | | | | |
| RI1 | | 0.8038 | | | | | | | | | |
| RI2 | | 0.8320 | | | | | | | | | |
| RI3 | | 0.7941 | | | | | | | | | |
| NA1 | | | | | 0.8966 | | | | | | |
| NA2 | | | | | 0.8139 | | | | | | |
| NA3 | | | | | 0.2502 | | | | | | |
| TR1 | | | | 0.5996 | | | | | | | |
| TR2 | | | | 0.4507 | | | | | | | |
| TR3 | | | | 0.6828 | | | | | | | |
| CI1 | | | | | | | | 0.8058 | | | |
| CI2 | | | | | | | | 0.6980 | | | |
| CI3 | | | | | | | | 0.3317 | | | |
| PB1 | | | 0.6447 | | | | | | | | |
| PB2 | | | 0.6446 | | | | | | | | |
| PB3 | | | 0.7822 | | | | | | | | |
| AI1 | 0.5340 | | | | | | | | | | |
| AI2 | 0.7758 | | | | | | | | | | |

| | |
|---|---|
| AI3 | 0.5847 |

**R-Squared**

| Construct | Coefficient of determination ($R^2$) | Adjusted $R^2$ |
|---|---|---|
| Adoption Intention | 0.4352 | 0.3960 |
| Perceived Benefit | 0.3221 | 0.3027 |
| Trustworthiness | 0.2836 | 0.2631 |

**Effect overview**

| Effect | Beta | Indirect effects | Total effect | Cohen's $f^2$ |
|---|---|---|---|---|
| RI -> AI | -0.0624 | | -0.0624 | 0.0045 |
| PB -> AI | 0.3763 | | 0.3763 | 0.1449 |
| TR -> AI | 0.2660 | | 0.2660 | 0.0686 |
| NA -> AI | 0.0683 | | 0.0683 | 0.0075 |
| RA -> AI | | 0.2294 | 0.2294 | |
| RA -> PB | 0.3911 | | 0.3911 | 0.1674 |
| RA -> TR | 0.3093 | | 0.3093 | 0.0991 |
| CO -> AI | | 0.1261 | 0.1261 | |
| CO -> PB | 0.1245 | | 0.1245 | 0.0174 |
| CO -> TR | 0.2679 | | 0.2679 | 0.0942 |
| CI -> AI | | 0.0943 | 0.0943 | |
| CI -> PB | 0.2268 | | 0.2268 | 0.0706 |
| CI -> TR | 0.0335 | | 0.0335 | 0.0015 |
| Gender -> AI | -0.1020 | | -0.1020 | 0.0171 |
| Age -> AI | -0.1109 | | -0.1109 | 0.0196 |
| Education -> AI | -0.0203 | | -0.0203 | 0.0007 |

**Total effect inference**

| Effect | Original coefficient | Standard bootstrap results | | | | | Percentile bootstrap quantiles | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean value | Standard error | t-value | p-value (2-sided) | p-value (1-sided) | 0.5% | 2.5% | 97.5% | 99.5% |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| RI -> AI | -0.0624 | -0.0617 | 0.0823 | -0.7590 | 0.4480 | 0.2240 | -0.2648 | -0.2337 | 0.1015 | 0.1540 |
| PB -> AI | 0.3763 | 0.3779 | 0.0843 | 4.4657 | 0.0000 | 0.0000 | 0.1489 | 0.2057 | 0.5373 | 0.5862 |
| TR -> AI | 0.2660 | 0.2669 | 0.0816 | 3.2610 | 0.0011 | 0.0006 | 0.0521 | 0.1037 | 0.4303 | 0.4783 |
| NA -> AI | 0.0683 | 0.0722 | 0.1041 | 0.6562 | 0.5119 | 0.2559 | -0.2135 | -0.1459 | 0.2448 | 0.3193 |
| RA -> AI | 0.2294 | 0.2304 | 0.0621 | 3.6970 | 0.0002 | 0.0001 | 0.0599 | 0.1114 | 0.3563 | 0.4119 |
| RA -> PB | 0.3911 | 0.3943 | 0.0944 | 4.148 | 0.0000 | 0.0000 | 0.1257 | 0.2021 | 0.5694 | 0.6060 |
| RA -> TR | 0.3093 | 0.3093 | 0.1148 | 2.6935 | 0.0072 | 0.0036 | 0.0287 | 0.0902 | 0.5370 | 0.5947 |
| CO -> AI | 0.1261 | 0.1265 | 0.0568 | 2.2183 | 0.0268 | 0.0134 | -0.0131 | 0.0184 | 0.2444 | 0.2809 |
| CO -> PB | 0.1245 | 0.1195 | 0.0936 | 2.3300 | 0.1838 | 0.0919 | -0.1053 | -0.0671 | 0.3038 | 0.3682 |
| CO -> TR | 0.2979 | 0.2999 | 0.1037 | 2.8714 | 0.0042 | 0.0021 | 0.0040 | 0.0827 | 0.4852 | 0.5379 |
| CI -> AI | 0.0943 | 0.1081 | 0.0501 | 1.8801 | 0.0604 | 0.0302 | -0.0110 | 0.0229 | 0.2080 | 0.2471 |
| CI -> PB | 0.2268 | 0.2425 | 0.0934 | 2.4284 | 0.0153 | 0.0077 | 0.0238 | 0.0665 | 0.4196 | 0.4847 |
| CI -> TR | 0.0335 | 0.0559 | 0.0850 | 0.3946 | 0.6933 | 0.3567 | -0.1654 | -0.1187 | 0.2269 | 0.2617 |
| Gender -> AI | -0.1020 | -0.1079 | 0.0785 | -1.2993 | 0.1942 | 0.0972 | -0.2987 | -0.2538 | 0.0508 | 0.0782 |
| Age -> AI | -0.1109 | -0.1019 | 0.0982 | -1.1288 | 0.2592 | 0.1296 | -0.3330 | -0.2840 | 0.0970 | 0.1410 |
| Education -> AI | -0.0203 | -0.0172 | 0.0800 | -0.2533 | 0.8001 | 0.400 | -0.2158 | -0.1688 | 0.1445 | 0.1903 |