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Eliciting Innovation Adoption Behaviour through Self-report and Peer-prediction Methods

Abstract

First, passive innovation resistance (PIR) is the tendency to resist new innovations before evaluating its potential. In this thesis PIR is measured with a 18 item scale of self-report survey questions conceptualized by previous researchers. Second, innate consumer innovativeness (ICI) reflects a person's predisposition and cognitive style towards innovation. ICI is measured by 6 survey questions asking people to predict the behaviour of their peers. Peer-prediction has been shown to reveal personal traits and preferences. Subsequently, the answers of each survey separately were used to classify people between early adopters and late adopters. Finally, I tested whether these classifications helped to explain respondent's willingness to pay (WTP) for an actual innovation. The WTP was elicited by the use of the Becker-DeGroot-Marschak method. Being classified as an early adopter based on the measures of PIR marginally significantly influenced to WTP to increase. In contrast, the classification of respondents between early and late adopters using the peer-prediction measures was not significantly associated with the WTP.

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1. Introduction

Nowadays, failure rates of new innovations can be as high as 90% (Barczak, Griffin, & Kahn, 2009), indicating that the vast majority of people might not necessarily feel the urge to seek novelty or try new products. This suggests that innate innovativeness is reserved for only a small group of innovators (Heidenreich & Handrich, 2015). Subsequently, there may be passive innovation resistance, where prior to evaluating the potential of an innovation the consumer shows resistance (Talke & Heidenreich, 2014). If this resistance is neglected this could lead to a substantial waste of billions of dollars in marketing expenses each year (Clancy, Krieg, & Wolf, 2006). Investments made in stages after the launch of a new innovation might be a waste if the prevalence of resistance is not revealed. Moreover, targeting people with high passive innovation resistance will most likely results in the failure of a new product (Swilley, 2010).

To improve the odds of success for new innovations it is necessary to study different methods that could reveal adoption related behaviour. Where the emphasis will be on passive innovation resistance and innate consumer innovativeness. In practice, some new innovations are tested to do well, but actually never take off. This could be explained by the known gap between expressed intentions and actual behaviour of consumers (Belk, 1985). On the individual level people could believe themselves to be more (less) innovative, whereas compared to others they might be more (less) reluctant in adopting new innovations. Potentially, this could be explained by certain behavioural traits. Through this thesis I want to study traits related to innovation adoption behaviour by examining two types of methods. Furthermore, within these methods I want to establish the existence of a dichotomy in early adopters and late adopters, influencing the willingness to adopt new innovations.

The first method is an 18 item scale on passive innovation resistance (PIR) conceptualized by Handrich & Heidenreich (2015). Their method was constructed to capture and justify the different dimensions of PIR. By performing multiple confirmatory factor analyses they provided evidence for several first- and second order dimensions of PIR. Moreover, their 18 item scale showed significantly high results in determining the dimensions of PIR. Therefore, I chose to test if this scale could also be used to classify individuals into high and low levels of PIR. Where the dichotomy in levels of PIR might partially explain an individual's adoption behaviour. Especially in this fast moving world, characterized by rapid change and new innovations, resistance could be of high importance to take into account. Consumers with a pro change attitude might need to be addressed in a different way compared to consumers who are more reluctant towards change. Hence, with no distinction in resistance attitudes, not all consumers will automatically evaluate new innovations in a positive way (Talke & Heidenreich, 2014).

The second method will be a new method conceptualized to determine if innate consumer innovativeness (ICI) can be elicited by prediction questions on the adoption behaviour of others. Previous researchers already established the usage of peer-predictions, combined with other constructs, to help determine the truth when no prior proxy is given (Prelec, Seung, and McCoy, 2017). It can also be used to reveal something about an individual's own preferences (Baillon, 2017). Moreover, in psychology 'the false consensus effect' explains an individual's tendency to overestimate the extent to which others share similar characteristics or preferences (Dawes, 1989). Given these findings, I expect answers to peer-prediction question to reveal a dichotomy in high and low predictions. When asked to predict the proportion of people adopting a new innovation, respondents with high ICI are expected to give higher predictions than respondents with low ICI. This dichotomy will be used as a proxy for innate consumer innovativeness, which could potentially explain an individual's adoption behaviour.

On both methods latent class analysis will be performed as this is a clustering method based on the prevalence of answer patterns within individuals, which is necessary to elicit hidden subgroups based on their characteristics (Lanza, Rhoades, Nix & Greenberg, 2010). Through the classification in high and low answer distributions established by this analysis the respondents will be clustered as either an early or a late adopter. This dichotomy seems reasonable since early adopters experience lower resistance to change compared to late adopters (Escobar-Rodriguez & Romero-Alonso, 2014), which is related to passive innovation resistance. Moreover, early adopters tend to actively seek for information which makes them more aware of potential benefits compared to late adopters (Hong & Zhu, 2006). This superior knowledge and awareness of innovations could indicate higher innate consumer innovativeness.

Overall, this is an exploratory study attempting to conceptualize a new method based solely on peer-predictions to determine the degree of innate consumer innovativeness. Subsequently, I examine the use of a conceptualized scale on passive innovation resistance as indicator for innovation adoption. Both the methods will be used to classifying respondents into early- and late adopters to provide an answer to the following research question:

Can actual innovation adoption behaviour better be elicited by clustered early and late adapters based on self-reported behavioural traits related to resistance or peer-prediction of innovation adoption?

2. Theoretical framework

2.1 Passive innovation resistance

To begin with, the adaption of new innovations is often described by the five stage decision model introduced by Rogers (2003). The first stage is the (1) knowledge stage, in which consumers become aware of the new innovation and are intrinsically motivated to seek further information. In the second stage, the (2) persuasion stage, consumers form an attitude towards the innovation, favourable or unfavourable depending on their own evaluation of the information gathered. Then, in the third stage, known as the (3) decision stage, consumers decide to either reject or adapt the new innovation. Moreover, in the fourth stage, consumers transform their intentions into actions as the innovation will be (4) implemented. Lastly, in the (5) confirmation stage, consumers choose to continue, stop or reverse their decision of adopting the innovation. This model by Rogers (2003) suggests that after the knowledge stage consumers automatically enroll in the persuasion stage, indicating pro change bias (Talke & Heidenreich, 2014).

However, consumers do not automatically enroll into the persuasion stage if consumers resist the innovation before evaluating the potential of the innovation, indicating passive innovation resistance (Talke & Heidenreich, 2014). When a new innovation creates pressure for alteration, passive innovation resistance results in behaviour to maintain the status quo (Bagozzi & Lee, 1999). Furthermore, passive innovation resistance depends on a certain inclination to resist change. This inclination depends on consumer specific factors which reflect fundamental behavioural traits (Nov & Ye, 2009). Oreg (2003) described a model of six behavioural traits to define the inclination to resist change. People show reluctance towards losing control, are closed minded and do not accept change, feel anxiety or stress due to change and do not want to experience higher effort in the short term as an adjustment to change. In addition, people have other preferences where some prefer novelty and innovation and others are not willing to give up old habits (Swilley, 2010). Furthermore, the inclination to resist change (IRC) is not caused by the product itself but by the changes it entails (Schein, 1985). In contrast, active innovation resistance does depend on product specific barriers that translates into non purchase behaviour (Laukkanen et al.,2008; Wiedmann et al., 2011).

To construct the framework of innovation resistance, previous literature suggests some consensus on the determinants that play a role in passive innovation resistance. Researchers have different opinions on the main determinant of PIR; some believe it is mainly driven by the inclination to resist change (IRC) (e.g., Antón, Camarero and Rodriguez, 2013), whereas others believe it is the satisfaction with the status quo (SQS) (e.g., Prins and Verhoef, 2007; Claudy, 2011) or even the combination of both (e.g., Bagozzi and Lee, 1999; Reinders, 2010). I have chosen to follow the PIR conceptualization of Heidenreich and Handrich (2015) which includes determinants of both IRC and SQS. This 18 item scale is chosen as it is the first scale to measure differences in consumers' levels of PIR. The scale consists of 12 items on IRC and 6 items on SQS. In addition, there are 6 dimensions consisting of 3 items each that either contribute to IRC or SQS. These dimension will now be discussed.

The IRC construct of this framework is in line with previous studies by Swilley (2010) and Talke and Heidenreich (2014). IRC consist of the following four dimensions obtained from Oreg's (2003) IRC personality traits. First, *Routine seeking behaviour (RS)* entails the tendency to maintain certain lifestyle routines due to the fear of losing control (Nov and Ye, 2008). Second, *Cognitive rigidity (CR)* represents a trait of dogmatism, which is characterized by an unwilling and inflexible attitude towards exploring new alternatives and concepts (Rokeach, 1960). Third, *Emotional reaction to change (ER)* is characterized by the limited ability of people the cope with change as a stressor (Swilley, 2010). At last, *Short term focus (STF)* refers to the tendency where people are focused on the disadvantages in the short-term instead of seeing the valuable advantages of innovations in the long-run (Oreg et al., 2008).

Subsequently, SQS is characterized by high satisfaction with the current situation. Here the tendency to use previously obtained products and show resistance towards new alternatives is experienced, resulting in lower probabilities of innovation adoption (Ellen et al., 1991). This construct consists of the following two dimensions. First, *Satisfaction with current products (SQSP)* inclines people to feel emotionally attached to the product they currently possess. This is due to the fact that they become acquainted with this product and use it repeatedly (Bagozzi and Lee, 1999). This attachment results in an experience of loss if people chose a new alternative over a tried and proven one. This experienced loss seems to outweigh the potential benefits of a new innovation (Hess, 2009). Second, *Satisfaction with the extent of innovation (SQSI)* leads to an increased attachment towards the status quo (Dethloff, 2004; Helm, 2001). Hence, if innovation evolves at a high rate it is difficult for people to process all the information and be able to compare all the available alternatives (Reinders, 2010). To summarize, if people are highly satisfied with the current products and the extent of innovation they are inclined to prefer the status quo over new alternatives (Claudy, 2011).

Finally, this conceptualized 18 item scale by Heidenreich and Handrich (2015) is the first empirical validation of PIR that combines IRC and SQS to determine an individual's predisposition to resist change. I expect this predisposition to resist change to affect an individual's adoption behaviour. Therefore, I choose to test if a dichotomy in high and low levels of PIR affects the willingness to pay for a new innovation. This dichotomy will be based on answers to the 18 item scale, which consists of 18 statements on behavioural traits related to PIR. For each statement respondents report how much they agree or disagree with the presented statements on a 7-point Likert scale. As people report their own personal trait, from now onwards this method will be referred to as the self-report method.

2.2 Peer-prediction methods

In this thesis a new method is introduced and tested to determine an individual's innate innovativeness. The method consists of prediction questions on the adoption behaviour of peers. This new method is chosen as predicting about others is said to reveal something about your own preferences and beliefs (Baillon, 2017). Moreover, in a lot of truth eliciting methods it is common practice to include expected distributions of the answers of peers. Prelec (2004) introduced the Bayesian Truth Serum (BTS), this method was developed to incentivize truthful answers to complex question where no prior proxy was given. The method consisted of a part where people answered about their own beliefs and a part where they had to bet on the distribution of the answers of their peers. Within this method people used their own answer as a proxy and predicted the true distribution of their peers to be relatively common. Furthermore, Prelec, Seung and McCoy (2017) applied a method to elicit the answer where people would be least surprised about if it were to be revealed. This method is mostly applied to questions were the majority may answer the question wrong. In this method people reveal their knowledge by predicting the answers of their peers given their own answer. If they give the true answer but predict others to choose the wrong answer they will be least surprised by the true answer.

The belief of economists that predictions on the behaviour of peers can be used as a proxy to find the truth, or as a tool to reveal people's preferences, is corroborated by what psychologists describe as the false consensus effect. The false consensus effect entails an individual's social projection whereby the degree of others sharing the same characteristics or beliefs is overestimated (Ross, Greene, & House, 1977). Dawes (1989) revealed the existence of this effect by comparing people's own endorsement on a certain topic to the predicted distribution of endorsement within a group these people belonged to. The predicted endorsement rates deviated from the actual endorsement rate in the direction of the respondent's own answer. Moreover, Bauman and Geher (2002) demonstrated that behavioural intentions towards sensitive societal issues can be predicted by the false consensus effect. Where relatively high estimates on the prevalence of certain behaviour of others significantly revealed the individual's own tendency to engage in this particular behaviour. For instance, disruptive innovations could cause imposed change to sensitive societal topics. Questions on these disruptive innovations might result in higher prevalence of the false consensus effect. Additionally, Hogset and Barret (2010) related this social projection to the framework of innovation adoption, where apparently the choice of an individual to adopt an innovation depends on their beliefs of the adoption behaviour of peers.

Based on the information above I would like to construct a new method solely based on peer-predictions to measure the innate consumer innovativeness (ICI) of a subject. Innate consumer innovativeness (ICI) is described as *"a generalized unobservable trait that reflects a person's inherently innovative personality, predisposition, and cognitive style"* (Im, Mason, and Houston, 2007, p. 64). ICI leads to innovative behaviours consisting of the tendency to seek more novelty (Steenkamp, Hofstede, and Wedel, 1999), explore new things (Cotte and Wood, 2004), and the inclination to buy new innovations quicker and more frequently compared to other people (Hirunyawipada and Paswan, 2006). I believe that a dichotomy in a high and low level of ICI could be revealed through peer-prediction questions. Literature on the false consensus effect and the truth eliciting methods suggests that people's own tendencies/preferences are at least partially revealed when predicting about others. Furthermore, Laukkanen et al. (2008) state that higher levels of PIR are evoked by radical innovations compared to incremental innovations. Therefore, the peer-prediction method will consist of peer-prediction questions on the adoption rate of both more disruptive and more incremental product innovations. At last, within this method high predictions on adoption behaviour of peers are assumed to indicate a higher level of ICI, whereas low predictions are assumed to indicate a lower level of ICI.

2.3 Adopter categories

The goal of this thesis is to measure the impact of both the methods in predicting actual innovation adoption. The answers to both the peer-prediction on ICI and the self-report method on PIR will be clustered into two adopter categories, namely early- and late adopters. Rogers (2003) described five adopter categories based on the timing and behavioural traits related to innovation adoption, consisting of innovators, early adopters, early majority, late majority and laggards. These five categories can be grouped into early and late adopters, where the early adopters are characterized by their openness to change (ICI) and the late adopters tend to show more resistance towards adopting new innovations (PIR) (Kim, Mirusmonoy, & Lee, 2010). Early adopters tend to actively seek for information to gain a better understanding of the potential benefits of the new innovation. Enhancing their ability to move faster from the knowledge stage into the decision stage (Hong & Zhu, 2006). Escobar-Rodriguez and Romero-Alonso (2014) found that early adopters have less resistance to change compared to late adopters, based on statements of reluctance and hesitation towards new innovations. In addition, Bruner and Kumar (2007) found that approximately half of the early adaptors in their sample, the so called gadget lovers, characterized by low scores of passive innovation resistance scored high on innate consumer innovativeness. In conclusion, these researchers show the possibility of clustering people based on their ICI and PIR into early- and late adopters. Nevertheless, a high score on PIR does not automatically indicate a low score on ICI, as well as a low score on PIR does not always indicate a high score on ICI. Therefore, I believe that the clusters of early and late adopters based on these scores will not be the same, with the following hypothesis:

H1: The clustered early and late adopters based on the self-report method and the peer-prediction method will not consist of entirely the same respondents.

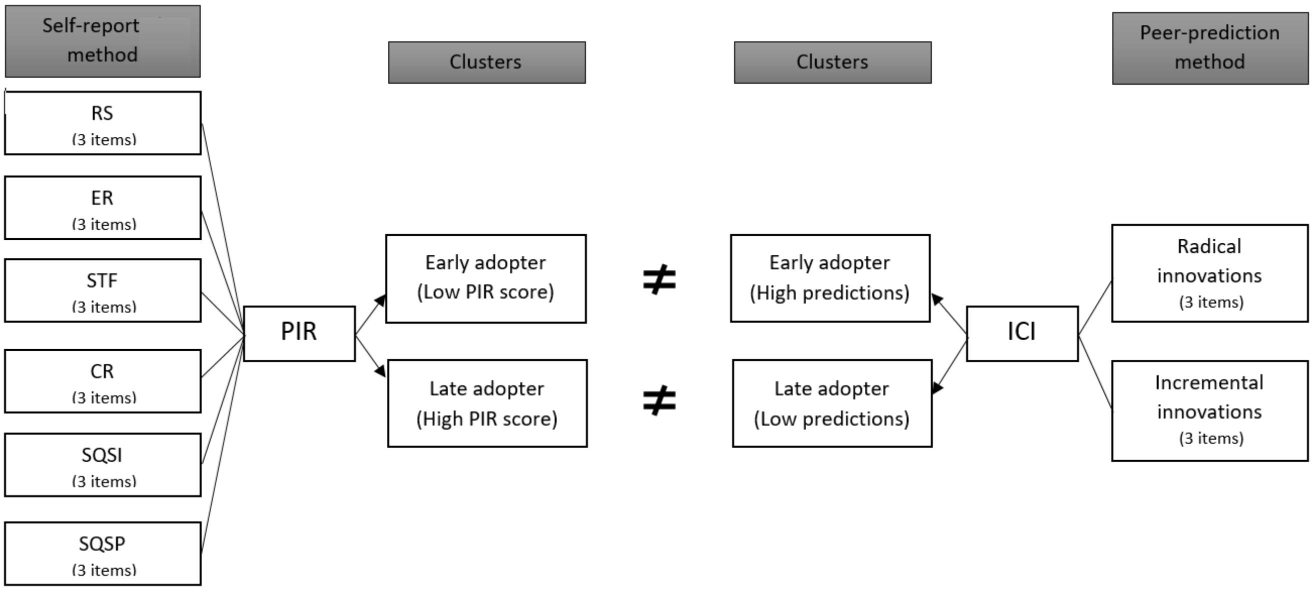


Figure 1. Framework clustering method and comparison

The Becker, De Groot and Marschak (1964) method is used to elicit the maximum willingness to pay for an actual innovation. By including such a measure it is possible to test which method works better in explaining the willingness to pay.

Numerous studies suggest that self-reported personality traits often show flawed results, as the self-view of people only shows a modest relationship with their actual behaviour (Dunning, Heath, and Suls, 2004). Furthermore, Epley and Dunning (2000) tested if people were more likely to have an accurate impression of their own positive personality traits, with a more cynical view of the traits of others, or if they had a more accurate impression of the behaviour of their peers, and overestimate their own positive traits. Their findings suggest that the latter seems to be the case. Hence, these studies suggest that the self-report method on the behavioural traits related to PIR might not be the most accurate in predicting someone's adoption behaviour. Accompanied by the more concrete questions on people's actions instead of their personality traits I believe that the peer-prediction method will provide a better proxy of the actual adoption behaviour. Therefore, the hypothesis will be as follows:

H2: The clustering based on the peer-prediction method can better explain the willingness to pay for innovation than the clustering based on the self-report method.

3. Data

3.1 Survey design

A survey was constructed consisting of four parts, namely a part for the peer-prediction method, the self-report method, the Becker, DeGroot and Marschak (BDM) method, and at last a part on demographics. The different parts were presented in this particular order except for the prediction and the self-report method parts. These parts were randomized in the survey design to account for possible order effects.

First, the peer-prediction method consisted of six questions on the prospective adoption behaviour of others. An example of such a prediction question on an incremental innovation is *"What percentage of people do you predict to acquire the latest new smartphone at least once every two years?"* or *"Imagine cultured meat becomes available in 2025 at the same price as regular meat, what percentage of people would actually move towards eating this lab-grown meat?"* as an example for a disruptive innovation (see Appendix A for all the survey questions). These questions had to be answered on a scale from 0 to 100.

Second, the self-report method consisted of 18 self-reporting items indicating passive innovation resistance based on 3 items per dimension (RS, CR, ER, STF, SQSP and SQSI). An example of one of the 3 items indicating routine seeking behaviour (RS) was *"I like to do the same old things rather than try new different ones."* which had to be answered on a 7-point Likert scale ranging from strongly disagreeing (1) to strongly agreeing (7) (see Appendix A for all the items on PIR). Preferring doing the same old things would most likely contribute to a higher resistance towards innovation.

Third, to measure the actual adoption behaviour respondents had to report their maximum willingness to pay for an actual innovation through the BDM method (See Section 3.2). Figure 2 shows the actual survey question. Figure 3 illustrates some of the answer possibilities to the question. The actual answer possibilities reached up to; €25 (you pay €25, keep €0).

Consider the following innovation: The Wake-up Light (worth around €25). The Wake-up Light is an alarm clock that simulates the sunrise (or sunset) to wake people up more gradually which will enhance their energy level in the morning. The Light has the following features: snooze function, digital FM radio, 6 different nature sounds, mood light function with 6 colors and 10 adjustable levels of light brightness.

One participant, randomly selected, will get €25. If you are this participant, you can decide to use part of the money to buy the Wake-up Light from me. The list below asks you whether you would buy it for various prices. Take your time and evaluate the options with care because your decision may be carried out for real.
This will work as follows: imagine you are the randomly selected participant; the computer will then draw at random a price for the Wake-up light between 1 and 25 euro. I will look at your decision for this price in the list below. If you choose not to buy the Wake-up Light then you keep the €25. If you buy the Wake-up Light, you will receive it, plus the remaining money.
NOTE: Fill in the option to buy/don't buy for all the prices presented below.

Figure 2. Survey question on WTP for innovation

	I Buy and get the product	I don't Buy and receive €25
€1 (you pay €1, keep €24)	○	○
€2 (you pay €2, keep €23)	○	○
€3 (you pay €3, keep €22)	○	○
€4 (you pay €4, keep €21)	○	○

Figure 3. Answer possibilities survey question on WTP for innovation

Last, the respondents had to answer questions on age, gender and education, as these could be used as control variables.

3.2 Becker, DeGroot and Marschak method

The Becker, DeGroot and Marschak (BDM) method was used to determine respondents' WTP. This method is said to be incentive compatible as respondents are inclined to bid their true willingness to pay (Breidert, 2007). In addition, Voelckner (2006) tested the BDM method to be effective in measuring the WTP of respondents as this measure showed significant high and positive correlations with respondents' actual demand on products. Furthermore, Wertenbroch and Skiera (2002) argued the BDM method to be a valid and reliable method in determining respondents' WTP. The participants in their experiments understood the procedure of the BDM method and were satisfied with the purchases through this method.

By using this method every respondent offered a price for a certain innovation. In the survey this was done through a trade-off matrix with buying decisions for every price between 1 and 25 euro. Afterwards, a price for the innovation was selected at random from this 1 to 25 distribution. If the offered price was above this randomly selected price, the respondent would not have received the innovation. In contrast, if the offered price was below the selected price then the respondent would have bought the innovation at the selected price. With this approach I tried to capture the actual WTP and not the hypothetical WTP, where actual WTP is measured when an actual purchase with payment is made (Voelckner, 2006). Therefore, the survey question was constructed as such, that one respondent was paid 25 euro for real to pay and receive the innovation if his or her offer was below the selected price.

3.3 Collected Variables

First, the data on the 18 PIR items consists of *Self_Report_i* for i in [q1_1 to q1_18]. The values range from 1 to 7 as it was measured on a 7-point likert scale. Second, the answers to the prediction questions are coded as *Peer_Prediction_i* for i in [q2_1 to q2_6]. The values are rounded numbers between 0 and 100. Third, the maximum willingness to pay for the innovation is captured by 25 buy or not buy decisions coded as *Choice_i,* i for 1 up till 25 euros [q3_1 to q3_25]. For all i from 1 to 25, the respondent indicated whether they preferred paying €i and get the product (keep €(25-i)) or not getting the product (and keeping €25). Fourth, *Self_Report_i for i is [q1_13 to q1_15]* represent the SQSP items of PIR. In the survey the formulation of the questions measured PIR in the opposite direction. To correct for this the answers to these items on the 7-point Likert scale were reversed. Finally, data was collected on age, gender and education. *Age* is a continuous variable with rounded values between 18 and 54. *Female* is a dummy variable with value 1 for female, and value 0 for male. *Education* is a categorical variable presenting the highest attained educational level of the respondent.

3.4 Computed Variables

Willingness to pay (WTP) is a continuous value between 0 and 25 euro, revealing the highest price the respondent was willing to pay for the innovation presented in the survey. The maximum is 25 euros as this was the actual price of the innovation. Respondents were offered multiple choices between keeping the money or the decision to buy the innovation at a certain price. All the answers to *Choice_i* are transformed into one variable. The WTP is defined as the maximum price i for which the respondent accepted paying i and get the product.

To obtain the groups of early and late adopters Latent Class Analysis (LCA) is performed. LCA is a statistical method that identifies hidden subgroups in data (further explained in Section 4.2). The main idea of this method is that it makes subgroups of respondents such that people within each group have answers as close as possible to each other, but that the different groups are as different as possible from each other. Performing LCA gives a probability that each respondent belongs to any of the two groups. Respondents will be assigned to their most likely group, either the group of early or late adopters.

By applying LCA to the *Self_Report_i* variables I obtained the variable *Probability early adopter PIR.* This variable shows the probability of the respondent belonging to the group of early adopters and takes on values between 0 and 1. Values closer to 1 indicate a higher possibility of belonging to the adopter category. Based on this probability I generated *Early adopter PIR* which represents the clustering based on the 18 item scale of PIR. If *Probability early adopter PIR* is above 0.5 the variable takes on the value 1 and classifies the respondent as an early adopter. Subsequently, if *Probability early adopter PIR* is below 0.5 the variable takes on the value 0 and classifies the respondent as a late adopter.

In addition, the same description applies to the variables *Probability early adopter ICI* and *Early adopter ICI,* which were obtained by applying LCA to the *Peer_Prediction_i* variables. Note that to perform tests on both methods it is not necessary to generate the cluster variables *Early adopter PIR* and *Early adopter INI*. It is also possible to use the individual probabilities *Probability early adopter PIR* and *Probability early adopter INI* directly.

The variable *Prediction Score Incremental* is the sum of all the answers to the prediction questions on incremental innovations. Whereas the variable *Prediction Score Disruptive* is the sum of all the prediction questions on disruptive innovations.

3.5 Sample

The data was collected online through a survey distributed to family, colleagues and friends in the first two weeks of May 2019. In total the sample included 81 respondents, consisting of mainly students and postgraduates aged between the 18 and 36 years old. The descriptive statistics show that 56.8% of the respondents were female and 43.2% were male. Hereby, 43.2% of the respondents obtained a bachelor degree as highest educational level and 40.7% obtained a master degree.

3.5. Variable overview

Table 1: Descriptive statistics variables

Variables	Explanation	Min	Mean	Max
WTP	The maximum amount of euros willing to pay for the selected innovation (Wake-up Light)	0	11.69	25
Early adopter PIR	Dummy variable describing the clustering based on the self-report method on PIR, 1=Early adopter and 0=Late adopter	0	.57	1
Early adopter ICI	Dummy variable describing the clustering based on the peer-prediction method on ICI, 1=Early adopter and 0=Late adopter	0	.38	1
Probability early adopter PIR	The probability score of belonging to the early adopters based on the LCA performed on the 18 items scale of PIR	.00	.37	1
Probability early adopter ICI	The probability score of belonging to the early adopters based on the LCA performed on the peer-prediction method indicating ICI	.00	.57	1
Female	Dummy variable describing the gender of the respondent, 1= female and 0=male	0	.57	1
Age	Continuous variable describing the age of the respondent	18	25.25	54
Education	Categorical variable describing the highest attained educational degree, 0=high school degree, 1=Secondary vocational education degree, 2=bachelor degree, 3=master degree, 4=professional/doctoral degree	0	2.30	4
Prediction score Disruptive	Sum of the three predictions on disruptive innovations	39	127.21	233
Prediction score Incremental	Sum of the three predictions on incremental innovations	22	117.25	235

4. Statistical analysis

4.1 Confirmatory factor analysis

The self-report method is based on the conceptualization of the 18 item scale of PIR by Heidenreich and Handrich (2015). In this study the scale development started off with 29 items to measure PIR, through either IRC dimensions (RS, ER, CR and STF) or SQS dimensions (SQSI and SQSP). By repeatedly assigning these items to the different dimensions of PIR, by both experts in a small scale study and students in a large scale study, they settled on the current 18 items with 3 items per dimension. Each item showed highly significant correlations towards the hypothesized dimensions of PIR.

To confirm if these items indeed fit the hypothesized dimensions of PIR, confirmatory factor analyses were performed per dimension using maximum likelihood estimates. Confirmatory factor analysis (CFA) is a statistical method to test whether indicators of a certain construct are in line with the researchers' understanding of the construct. In this case, the items per dimension are tested to have similar patterns in responses. The patterns are suggested to be similar since these items are associated with the same latent dimension. Through CFA factor loadings are obtained per item, which express the relation between the item and the underlying dimension. A factor loading above 0.5 makes an item a reliable indicator for the latent dimension (Homburg and Giering, 2001).

The analysis by Heidenreich and Handrich (2015) presented an evident factor pattern of every 3 items related to their dimensions of PIR. As I use the same 18 item scale on PIR in the survey it allows me to replicate the confirmatory factor analysis and test if similar results can be found. The replicated framework of these confirmatory factor analyses can be found in the Appendix.

4.2 Latent class analysis

The latent class analysis (LCA) method is used to identify hidden subgroups, of individuals similar to each other based on certain characteristics in their behaviour. The latent variable, if the respondent is more inclined to be an early or a late adopters, is not directly measured. However, the questions on the self-report and peer-prediction method function as indicators to reveals this hidden adopter category. Within LCA the classification of the data in subgroups is based on the pattern of answers to categorical indicators. The purpose of this method is to minimize the distance between the answers to the different indicators within groups and maximize this distance between groups. Figure 4 illustrates a simple example of data points that are grouped together to visualize how this method works. In this example we can see a clear pattern where answers close to each other are grouped together, whereas different groups are clearly separated from each other. Moreover, this method focusses less on interactions between variables, but more on the structure of the groups (Glen, 2015).

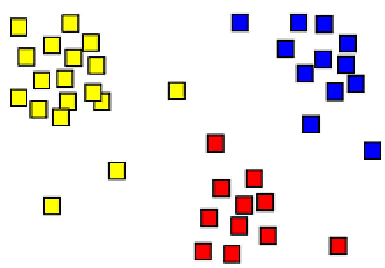


Figure 4: Example hidden subgroups in data (Glen, 2015)

The use of this method is justified for complex constructs that measure multiple observed behaviours. This is the case for both the peer-prediction and the self-report method. Furthermore, LCA provides an understanding on how these multiple characteristics and behaviours interact within individuals. In contrast to other factor analysis approaches that assess the latent class variable to be continuous and variable-centered, LCA assesses this variable to be categorical and more individual-centered (Lanza, Rhoades, Nix & Greenberg, 2010). A individual-centered approach seems necessary if we want to classify people on their attitude towards innovation. Their adopter category is more likely to be captured by focusing on the relation between different individuals than focusing on the relation between different variables. Since the classification of adopter categories is explained by individual characteristics it seems reasonable to perform LCA on the 18 item scale of PIR and the peer-prediction questions indicating ICI. Hereby, LCA is performed to create two separate classes, namely the dichotomy in early and late adopters. By performing LCA it creates two new variables, one for each class, with a probability of belonging to that specific class between 0 and 1. Based on these variables the clustering is performed, if the probability is above 0.5 respondents are assigned to the corresponding adopter category.

4.3 Comparing clusters

To compare *Early adopter ICI* and *Early adopter PIR* the Chi-square test of independence was chosen. This test is used to determine if there is a significant relationship between two categorical variables. The frequency of being clustered an early adopter in one method is compared to being clustered an early or late adopter in the other method. The null hypothesis for this test suggests that there is no relationship between the two clusters. The alternative hypothesis is that there is a relationship between both the clusters.

In addition, the clusters were computed with the probability variables gathered from the latent class analysis performed on both methods. These variables, *Probability early adopter* and *PIR Probability early adopter ICI*, show probabilities between 0 and 1 at ordinal scale, and therefore, allow for the Spearman rank correlation test. The Spearman correlation test is used to measure the degree of association between variables. In this case on the probability of belonging to the same adopter category in both methods.

4.4 Multiple linear regression

To answer the hypothesis on which method works better in explaining the actual adoption behaviour of consumers, multiple linear regressions have been performed to study the effect of the clusters on the willingness to pay for innovation. This method was chosen as it is used as a predictive analysis that explains the relationship between a continuous dependent variable, in this case WTP, and two or more independent variables, such as the clusters and the control variables.

5. Results

5.1 Raw data description

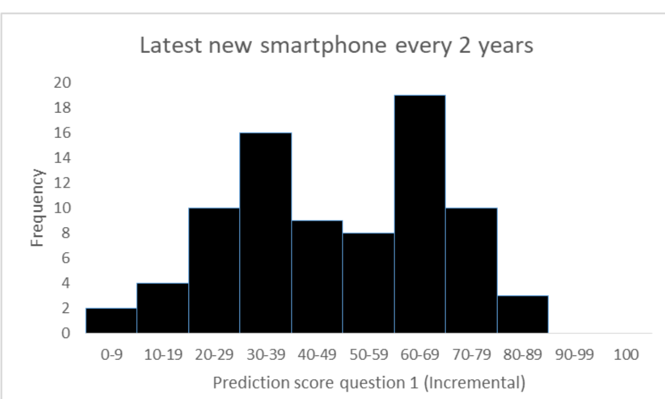
Table 2 shows the descriptive statistics on the PIR scale items. The first 12 items measure the inclination to resist change (IRC) and the last 6 items measure the satisfaction with the status quo (SQS). Findings on the items seem in line with this dichotomy. On the first 12 items the respondents were less likely to ‘agree’ (6) or ‘totally agree’ (7) with the items compared to the other answer options. Whereas for the last 6 items respondents never ‘totally disagreed’ (1) and were less likely to ‘disagree’ (2) with the items on satisfaction with the status quo compared to the other answer options. This suggests that there is a difference in the pattern of answers between the dimensions.

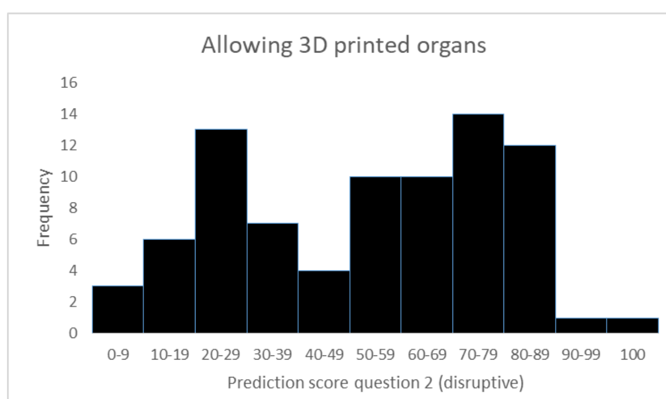
The answers on routine seeking behaviour (RS) are characterized by high frequencies within the second and third point scale options, indicating that the respondents disagreed more than agreed with these statements. In contrast, the answers on the emotional reaction to change (ER) provided more spread across the scale options, where the highest frequencies where on either ‘disagreeing’ (2) or on ‘somewhat agreeing’ (5), but less on extremes. Items on short term focus (STF) showed the highest frequencies for ‘disagreeing’ (2) or ‘somewhat disagreeing’ (3), but also indicate a high frequency for ‘somewhat agreeing’ (5). Surprisingly, the answers on the cognitive rigidity (CR) items show a more equal spread over the middle options excluding the extremes, which does not indicate a particular pattern of either agreeing or disagreeing with these items. Finally, the last six items on satisfaction with the current extent of innovation (SQSI) and products (SQSP) showed a similar pattern. Here the answers distribution were the highest for ‘neutral’ (4), ‘somewhat agreeing’ (5) and ‘agreeing’ (6).

Table 2: Descriptive statistics PIR items

	Items	Frequencies of the 7-point Likert answers						
		1	2	3	4	5	6	7
RS	q1_1 - I generally consider changes to be a negative thing.	9 (11.1%)	43 (53.1%)	13 (16.1%)	10 (12.6%)	5 (6.2%)	1 (1.2%)	-
	q1_2 - I like to do the same old things rather than try new different ones.	5 (6.2%)	28 (34.6%)	19 (23.5%)	14 (17.3%)	13 (16.1%)	2 (2.5%)	-
	q1_3 - I'd rather be bored than surprised.	28 (34.6%)	30 (37%)	14 (17.3%)	5 (6.2%)	2 (2.5%)	1 (1.2%)	1 (1.2%)
ER	q1_4 - If I were to be informed that there's going to be a significant change regarding the way things are done at work, I would probably feel stressed.	8 (9.9%)	22 (27.2%)	16 (19.8%)	16 (19.8%)	16 (19.8%)	3 (3.7%)	-
	q1_5 - When I am informed of a change of plans, I tense a bit up.	7 (8.6%)	16 (19.8%)	16 (19.8%)	14 (17.3%)	23 (28.4%)	4 (4.9%)	1 (1.2%)
	q1_6 - When things don't go according to plans, it stresses me out.	2 (2.5%)	18 (22.2%)	14 (17.3%)	13 (16.1%)	22 (27.2%)	12 (14.8%)	-
STF	q1_7 - Often, I feel a bit uncomfortable even about changes that may potentially improve my life.	11 (13.6%)	23 (28.4%)	26 (32.1%)	8 (9.9%)	7 (8.6%)	5 (6.2%)	1 (1.2%)
	q1_8 - When someone pressures me to change something, I tend to resist it even if I think the change may ultimately benefit me.	6 (7.4%)	25 (30.9%)	22 (27.2%)	7 (8.6%)	16 (19.8%)	5 (6.2%)	-
	q1_9 - I sometimes find myself avoiding changes that I know will be good for me.	8 (9.9%)	27 (33.3%)	17 (21%)	6 (7.4%)	17 (21%)	6 (7.4 %)	-
CR	q1_10 - I often change my mind.	-	21 (25.9%)	15 (18.5%)	15 (18.5%)	10 (12.4%)	19 (23.5%)	1 (1.2%)
	q1_11 - I don't change my mind easily.	1 (1.2%)	14 (17.3%)	20 (24.7%)	14 (17.3%)	20 (24.7%)	12 (14.8%)	-
	q1_12 - My views are very consistent over time.	-	7 (8.6%)	17 (21%)	18 (22.2%)	26 (32.1%)	11 (13.6%)	2 (2.5%)
SQSI	q1_13 - Overall, my personal need for innovations in the field of technological products has been by far not covered in the past. (r.)	-	2 (2.5%)	7 (8.6%)	28 (34.6%)	17 (21%)	23 (28.4%)	4 (4.9%)
	q1_14 - Overall, I consider the number of innovations in the field of technological products as being too low. (r.)	-	1 (1.2%)	12 (14.8%)	21 (25.9%)	18 (22.2%)	23 (28.4%)	6 (7.4%)
SQSP	q1_15 - Overall, I consider the pace of innovations in the field of technological products as being too low. (r.)	-	2 (2.5%)	11 (13.6%)	17 (21%)	21 (25.9%)	25 (30.9%)	5 (6.2%)
	q1_16 - In the past, I was very satisfied with available technological products.	-	2 (2.5%)	7 (8.6%)	12 (14.8%)	24 (29.6%)	33 (40.7%)	3 (3.7%)
	q1_17 - In my opinion, past technological products were completely satisfactory so far.	-	8 (9.9%)	7 (8.6%)	19 (23.5%)	23 (28.4%)	21 (25.9%)	3 (3.7%)
	q1_18 - Past technological products fully met my requirements.	-	8 (9.9%)	10 (12.4%)	22 (27.2%)	21 (25.9%)	17 (21%)	3 (3.7%)

Figure 4 shows the distributions of the answer to the prediction questions in separate histograms. In general, a similar pattern can be recognized within the distributions. The data can be split into two groups, one with frequent low predictions, and one with frequent high predictions. However, looking at the histograms separately provides a more detailed description of the distribution towards different types of innovation. The first histogram on acquiring a new smartphone once every two years provides the clearest dichotomy in high and low predictions. With a clear threshold around 50 percent. The histogram on allowing for 3D printed organs shows surprisingly high prediction scores. The majority of respondents predicts more than 50 percent of the people to allow for this innovation into their body. Nevertheless, there is still a clear group of respondents that provides lower scores. The histogram on the usage of virtual home assistants is the only prediction question that provides a unimodal distribution of low predictions. Here no clear dichotomy can be found. The prediction answers on the histogram of allowing AI to take over half the workforce by 2015 shows more centered predictions. Predictions go up to approximately 70 percent with a threshold for the dichotomy around 30 percent. Furthermore, the question on the usage of bio trackers in everyday life provides a high frequency of very low predictions on an interval of 0 to 39 percent, but also a group of somewhat higher predictions at the interval of 50 to 69 percent. The last histogram on the move towards lab-grown meat instead of normal meat provides low predictions at the interval of 20 to 39 percent. However, still one third of the respondents report predictions above 50 percent on this question.





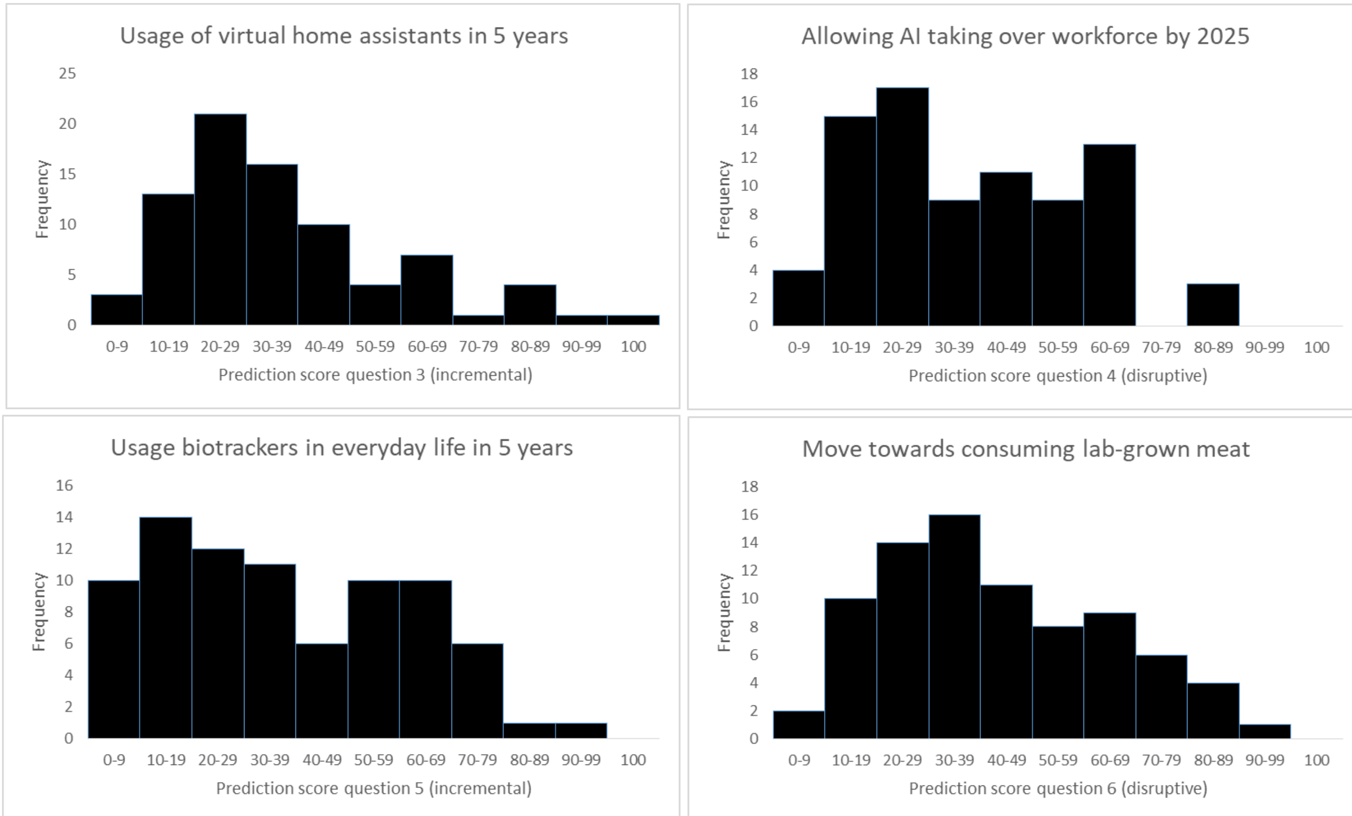


Figure 4. Histograms on the distribution of answers to the peer-prediction questions

To examine the peer-prediction method even further the relevance of classification on incremental versus disruptive innovations is explored. A paired samples t-test is conducted on *Prediction score Disruptive* and *Prediction score Incremental* to compare if there is a difference in the values of these prediction questions. This test is performed as previous research suggests that disruptive innovations compared to incremental innovations cause higher levels of resistance (Laukkanen et al., 2008), and provides stronger expressions of the false consensus effect (Bauman & Geher, 2002). These findings suggest that the predictions on disruptive innovations might differ from the predictions on incremental innovations. The results on this paired t-test show that there is no significant difference in the prediction score for the disruptive innovations ($M=127.21$, $SD=45.41$) and the incremental innovations ($M=117.25$, $SD=48.67$) conditions; $t(80) = 1.54$, $p = .13$. However, the one-sided outcome of the paired t-test, indicating that the mean difference of disruptive and incremental innovations is greater than zero shows a marginally significant outcome ($p = .06$). These findings suggest that their might be some evidence that in the peer-prediction method questions respondents predict higher values on disruptive innovations compared to incremental ones.

5.2 Confirmatory factor analysis on the PIR scale

The confirmatory factor analysis performed by Heidenreich and Handrich (2015) is replicated to check if similar results can be obtained. Table 3 compares the factor loadings reported by Heidenreich and Handrich (2015) with those obtained on the data of the present thesis. First, when comparing the two analyses the means appear to be quite similar in values and seem to follow a similar pattern. However, the factor loadings seem to deviate from each other. The factor loadings of Heidenreich and Handrich (2015) are substantially higher than the loadings I obtained. These lower loadings do not necessarily form a problem, since factor loadings above the 0.5 threshold are proven to be reliable indicators (Homburg and Giering, 2001). Surprisingly, item 3 on routine seeking behaviour and items 11 and 12 on cognitive rigidity do not seem to pass this threshold value and seem unreliable indicators in determining their accompanied dimension within the new survey sample. The fact that the factor loadings are lower and do not all pass the threshold value might be due to the smaller sample size. In this thesis I only have 81 observations compared to the 367 observations of Heidenreich and Handrich (2015).

Table 3: Scale items Confirmatory Factor Analysis

Dimension	Item	Confirmatory Factor Analysis (2015)		Confirmatory Factor Analysis Replication	
		Mean (*SD*)	Factor Loading	Mean (*SD*)	Factor Loading
RS	q1_1 - I generally consider changes to be a negative thing.	2.52 (1.43)	.85	2.53 (1.12)	.57
	q1_2 - I like to do the same old things rather than try new different ones.	2.77 (1.53)	.85	3.10 (1.28)	.77
	q1_3 - I'd rather be bored than surprised.	2.93 (1.69)	.68	2.14 (1.22)	**.43**
ER	q1_4 - If I were to be informed that there's going to be a significant change regarding the way things are done at work, I would probably feel stressed.	3.16 (1.65)	.89	3.23 (1.40)	.71
	q1_5 - When I am informed of a change of plans, I tense a bit up.	3.26 (1.63)	.89	3.57 (1.48)	.85
	q1_6 - When things don't go according to plans, it stresses me out.	3.44 (1.72)	.89	3.88 (1.47)	.75
STF	q1_7 - Often, I feel a bit uncomfortable even about changes that may potentially improve my life.	2.75 (1.47)	.89	2.95 (1.43)	.68
	q1_8 - When someone pressures me to change something, I tend to resist it even if I think the change may ultimately benefit me.	2.88 (1.54)	.87	3.21 (1.42)	.54
	q1_9 - I sometimes find myself avoiding changes that I know will be good for me.	3.24 (1.63)	.86	3.19 (1.52)	.75
CR	q1_10 - I often change my mind.	4.07 (1.63)	.78	3.93 (1.56)	.88
	q1_11 - I don't change my mind easily.	3.44 (1.56)	.89	3.91 (1.38)	**-.74**
	q1_12 - My views are very consistent over time.	3.14 (1.50)	.84	4.28 (1.26)	**-.47**
SQSI	q1_13 - Overall, my personal need for innovations in the field of technological products has been by far not covered in the past.	4.35 (1.97)	.91	4.79 (1.17)	.51
	q1_14 - Overall, I consider the number of innovations in the field of technological products as being too low.	4.72 (1.83)	.96	4.84 (1.24)	.87
	q1_15 - Overall, I consider the pace of innovations in the field of technological products as being too low.	4.71 (1.86)	.94	4.88 (1.24)	.83
SQSP	q1_16 - In the past, I was very satisfied with available technological products.	4.70 (1.58)	.97	5.09 (1.13)	.59
	q1_17 - In my opinion, past technological products were completely satisfactory so far.	4.61 (1.60)	.97	4.63 (1.33)	.77
	q1_18 - Past technological products fully met my requirements.	4.56 (1.68)	.96	4.47 (1.32)	.86

SD, standard deviation

5.3 Latent class analysis

Table 4 shows the results of the LCA on the peer-prediction questions. The LCA specifies two classes based on the innate innovativeness of the respondents. Overall, the first class is defined by lower marginal means than the second class. Therefore, belonging to the first class, which predicts lower values, classifies respondents as late adopters. Belonging to the second class classifies respondents to be early adopters. In contrast, question 2 of the peer-prediction method does not follow this pattern and shows a higher marginal mean in class one compared to class two. Moreover, the standard error of this question is also higher compared to the other question in both the classes. These higher standard errors indicate that there is a lot of spread in the answer distribution of this question which makes it a less reliable indicator for this method. To control for this particular pattern the LCA is performed without question q2_2. As Table 4 shows the exclusion of question q2_2 does not cause the values of the other prediction questions to change. Furthermore, a correlation test performed on the cluster variables for both methods shows a correlation of 0.99, indicating that both methods show similar results. Due to the high correlation of the methods, the method containing all the question is chosen for further analysis.

Table 4: Latent class analysis Peer-prediction Method

		LCA Peer-prediction Method		LCA Peer-prediction Method without q2_2	
		Marginal mean (SE)	95% Conf. Interval	Marginal mean (SE)	95% Conf. Interval
1					
q2_1	Latest new smartphone every 2 years	42.67 (2.96)	36.86-48.47	43.08 (2.90)	37.39-48.77
q2_2	Allowing 3D printed organs	**52.96** (3.81)	45.50-60.42		
q2_3	Usage of virtual home assistants	25.67 (3.59)	18.64-32.71	26.87 (3.61)	19.79-33.95
q2_4	Allowing AI taking over workforce	29.07 (2.72)	23.75-34.40	28.82 (2.58)	23.77-33.87
q2_5	Using bio trackers in everyday life	21.99 (2.33)	17.43-26.56	22.01 (2.18)	17.74-26.28
q2_6	Consuming lab-grown meat	38.73 (3.02)	32.81-44.64	38.80 (3.01)	32.89-44.71
2					
q2_1	Latest new smartphone every 2 years	**52.64** (3.88)	45.04-60.24	**52.19** (3.85)	44.64-59.73
q2_2	Allowing 3D printed organs	46.95 (5.12)	36.91-56.99		
q2_3	Usage of virtual home assistants	**51.02** (4.66)	41.88-60.17	**49.61** (4.55)	40.70-58.53
q2_4	Allowing AI taking over workforce	**46.67** (4.12)	38.60-54.74	**47.60** (4.07)	39.62-55.57
q2_5	Using bio trackers in everyday life	**59.15** (3.49)	52.31-65.99	**60.16** (3.64)	53.03-67.29
q2_6	Consuming lab-grown meat	**44.52** (4.01)	36.66-52.38	**44.55** (4.08)	36.56-52.54

SE, standard error

Table 5 shows the results of the LCA on the self-report method determining the level of passive innovation resistance of the respondents. The analysis classifies two classes, where the sum of the marginal means of the first class is lower than the sum of marginal means of the second class. As Table 5 shows not all the marginal means on the PIR scale items are higher in the second class only the first eleven. However, the first 11 items show more deviation than the last 7 items. This causes more weight on the total sum of the marginal means. Therefore, the second class can be classified by a higher level of PIR. Thus, belonging to the first class, indicating lower PIR scores, classifies respondents as early adopters. Whereas the respondents belonging to the second class, with higher PIR scores, are classified as late adopters.

Table 5: Latent class analysis Self-report Method

	LCA Self-report Method class 1 (early)		LCA Self-report Method class 2 (late)	
	Marginal mean (SE)	95% Conf. Interval	Marginal mean (SE)	95% Conf. Interval
q1_1	2.21 (.16)	1.91-2.52	**2.95** (.18)	2.59-3.31
q1_2	1.34 (.14)	2.06-2.62	**4.11** (.17)	3.78-4.45
q1_3	1.55 (.15)	1.25-1.84	**2.92** (.18)	2.56-3.28
q1_4	2.42 (.16)	2.09-2.74	**4.32** (.18)	3.96-4.68
q1_5	2.91 (.19)	2.53-3.28	**4.45** (.22)	4.02-4.88
q1_6	3.27 (.20)	2.88-3.66	**4.68** (.22)	4.25-5.12
q1_7	2.53 (.20)	2.13-2.92	**3.51** (.24)	3.04-3.98
q1_8	2.67 (.19)	2.30-3.05	**3.92** (.22)	3.49-4.36
q1_9	2.71 (.21)	2.29-3.13	**3.81** (.26)	3.31-4.32
q1_10	3.92 (.23)	3.47-4.37	**3.93** (.27)	3.41-4.46
q1_11	3.77 (.20)	3.37-4.17	**4.11** (.24)	3.65-4.57
q1_12	**4.33** (.19)	3.96-4.69	4.22 (.22)	3.80-4.66
q1_13	**5.10** (.17)	4.77-5.43	4.38 (.19)	4.00-4.76
q1_14	**5.19** (.18)	4.85-5.54	4.37 (.21)	3.97-4.77
q1_15	**5.31** (.17)	4.98-5.64	4.30 (.20)	3.91-4.68
q1_16	**5.13** (.17)	4.80-5.46	5.03 (.19)	4.65-5.41
q1_17	**4.70** (.20)	4.31-5.09	4.54 (.23)	4.09-4.99
q1_18	**4.60** (.20)	4.22-4.99	4.29 (.22)	3.85-4.74

SE, standard error

In addition, the study by Handrich and Heidenreich (2015) showed that the first 12 items on the IRC were better measures for PIR that the last 6 items on the SQS, which justifies my classification of early and late adopters. However, it is surprising to see that the group which is classified as late adopters does not have higher means on all the items indicating PIR compared to the group of early adopters. It might be necessarily to further explore why not all these items show higher means for the latent class of late adopters. Therefore, I examined if a similar pattern could be found in the answers to this 18 items scale for the people that were classified based on their answers to the peer-prediction method. The last 6 items represent the satisfaction with the status quo of current products (q1_16 to q1_18) and the extent of innovation (q1_13 to q1_15). These items are more in line with the peer-prediction question as they are more directly related to products and innovations instead of personal traits. This might suggest that the classification of the peer-prediction method is more in line with the higher means on the last 6 items of the PIR scale.

Table 6 shows the means in the 18 item scale of PIR within the clustering based on the peer-prediction method. There is some indication of a similar pattern where there is a pivot point around the eleventh item. However, for the items indicating the satisfaction with current products (q1_16 to q1_18) the means are higher for the early adopters compared to the late adopters, which is surprising to see. This means that in both methods higher marginal means to the questions on the satisfaction with current products (SQSP) indicate belonging to the group of early adopters based on the LCA. This finding suggests that a higher satisfaction with current products implies more willingness to adopt new innovations, which contradicts previous literature. For instance, Bagozzi and Lee (1999) argued that a higher satisfaction with a current product results in more emotional attachment, resulting in an experienced loss if the current product is replaced.

Table 6: Means on the 18 item scale of PIR by the peer-prediction clustering

Item	Late adopters peer-prediction method Mean (SD)	Early adopters peer-prediction method Mean (SD)
q1_1	2.46 (1.15)	**2.65** (1.08)
q1_2	2.96 (1.23)	**3.32** (1.35)
q1_3	1.94 (1.06)	**2.45** (1.36)
q1_4	3.08 (1.45)	**3.48** (1.29)
q1_5	3.38 (1.43)	**3.87** (1.54)
q1_6	3.78 (1.46)	**4.03** (1.49)
q1_7	2.76 (1.36)	**3.26** (1.50)
q1_8	3.02 (1.35)	**3.52** (1.50)
q1_9	3.16 (1.52)	**3.25** (1.54)
q1_10	3.92 (1.47)	**3.94** (1.71)
q1_11	**4** (1.36)	3.77 (1.43)
q1_12	**4.32** (1.15)	4.23 (1.43)
q1_13	**4.88** (1.21)	4.65 (1.11)
q1_14	**4.94** (1.17)	4.68 (1.35)
q1_15	**5.06** (1.08)	4.58 (1.43)
q1_16	5.08 (1.16)	**5.09** (1.11)
q1_17	4.48 (1.40)	**4.87** (1.18)
q1_18	4.4 (1.31)	**4.58** (1.36)

SD, standard deviation

5.3 Chi square test of independence and Spearman correlation test

A Chi-square test of independence is calculated to test if the frequency of being clustered as an early or late adopter in the self-report method is independent of the clustering based on the peer-prediction method. Hereby, a significant interaction is found (χ^2 (1) = 4.52, $p < .05$) indicating that clustering based on the different methods are significantly related to each other. In addition, a Spearman rho's test is performed on the probability scores of being clustered as an early adopter obtained by the LCA on both methods. A significant negative interaction between both the probabilities is found $r_s = -.27$, $p < .05$ indicating that being a late adopter in one cluster is negatively correlated with being a late adopter in the other cluster. Therefore, we can conclude that both clusters based on the peer-prediction and self-report methods are significantly dependent on each other. However, they provide different distributions of early and late adopters across the same sample. In addition, through the negative correlation a pattern can be recognized. Respondents that are more likely to be an early adopter based on one method are more likely to be a late adopter in the other method. This finding seems surprising as both methods are argued to provide a proper classification of early and late adopters based on either high ICI or low PIR. The scatterplot on *Probability early adopter PIR* and *Probability early adopter ICI* in Figure 5 illustrates that the majority of respondents is classified as early adopter in one method, and as late adopter in the other. This contradictory finding might indicate that solely one method is giving the right proxy of early adopters in this sample. Therefore, it is necessary to test which method can better explain the WTP in the following section.

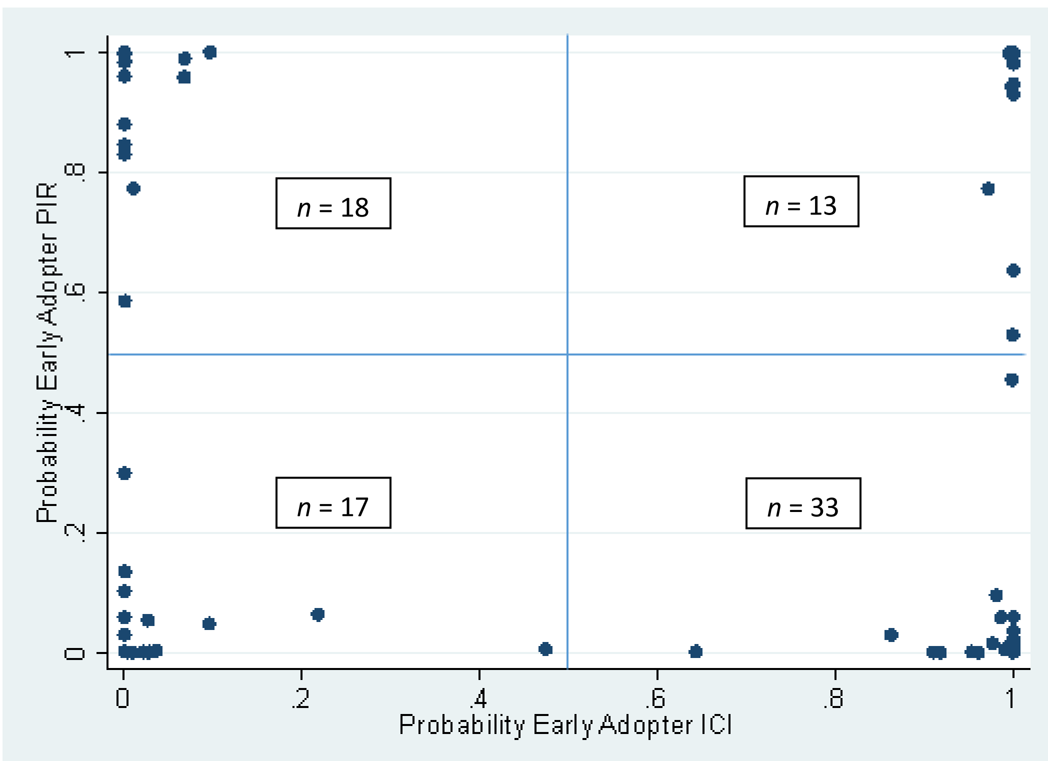


Figure 5. Scatterplot probabilities of being an early adopter based on ICI and PIR

5.4 Multiple regressions on WTP

A multiple linear regression is performed to predict the willingness to pay for innovation based on the clustered early adopters on both the self-report and the peer-prediction method, including the control variables. A marginally significant regression equation was found (F (5, 75) = 2.13, p < .1), with an R^2 of .10. Being clustered as early adopter based on the self-report method is a marginally significant indicator of the willingness to pay for innovation. In contrast, the clustering based on the peer-prediction method did not show significant results. The willingness to pay for innovation increased (decreased) by 3.16 euros if the respondent was clustered as an early (late) adopter compared to a late (early) adopter based on their PIR, marginally significant at 10%. In addition, Table 7 presents multiple regressions, including regressions with solely one of the indicators of being clustered as early adopter. The findings on the different regressions stay approximately the same compared to the regression including both the indicators.

Table 7: Multiple regressions analysis

WTP	Clusters based on CLA			Robustness check CLA probabilities			Robustness check SR cluster 3 categories	
(Constant)	**9.54****	**6.73***	**7.45***	6.17	**7.49***	**6.57***	5.38	
Early adopter PIR (Self-report)	**3.16***	**-3.02***					4.28 **4.90*****	(vast majority) (early adopter)
Early adopter ICI (Peer-prediction)	.76		.11					
Probability early adopter PIR				**3.62***		**.3.42***		
Probability early adopter ICI				.93	.00			
Age	-.06	-.06	-.04	-.07	-.04	- 0.06	-0.05	
Female	.86	1.03	.84	.84	.86	1.01	.88	
Education	**1.87****	**1.83****	**2.08****	**1.86****	**2.07****	**1.81****	**1.78****	
	R^2: 0.10 F: 2.13*	R^2: 0.09 F: 2.48*	R^2: 0.06 F: 1.37	R^2: 0.10 F: 2.33*	R^2: 0.06 F: 1.37	R^2: 0.10 F: 2.71**	R^2: 0.15 F: 2.92**	

N = 81, * p < .1, ** p < .05, *** p < .01

Furthermore, robustness checks are performed to check for this marginally significant effect of the clustering based on the self-report method. The first robustness check includes solely the probabilities of being an early adopter obtained from the LCA. These probabilities are used since these variables represent more continuous values between 0 and 1 compared to the binary clusters. For this robustness check Table 7 shows a marginally significant regression equation ($F(5,75) = 2.33$, $p < .1$), with an R^2 of .10 similar to the regression performed based on the clusters. Likewise, the willingness to pay for innovation increases by 0.0362 euros if the respondent has one percent higher probability of belonging to the early adopters based on his or her PIR, marginally significant at 10%. As the distribution of the probabilities of being an early adopter was centered around 0.99 we can say that being very sure that a respondent is clustered as an early adopter increases the willingness to pay by approximately 3.62 euros.

For the second robustness check, a new cluster is constructed. Only respondents with a probability of belonging to a certain adopter category above 0.95, are classified as early- and late adopters. For the respondents that cannot be assigned to either of the adopter categories (probabilities below 0.95) a new 'vast majority' category is created. This new category falls between the two other categories. Hence, only the respondents that are very likely to be in either the early- or late adopter categories get assigned to these categories. Hereby, the respondents that are less likely belong to an intermediate category. Including the new self-report cluster based on 3 adopter categories provides a significant regression equation ($F(7, 73) = 2.92$, $p < .05$), with an R^2 of .15. Hereby, the willingness to pay increases (decreases) by 4.90 euros if a respondents is clustered as an early (late) adopter compared to a late (early) adopter based on their PIR, significant at 5%. Moreover, no significant result is found on the WTP for respondents in the vast majority compared to the late adopters.

Additionally, in all the regressions education seems to have a significant positive effect on the WTP. The willingness to pay increases by approximately 1.80 euros if the respondent obtains one educational level higher, significant at 5%. The other control variables do not influence the WTP significantly.

6. Conclusion and discussion

In this thesis I examined different methods that could potentially give a proxy of a dichotomy in early and late adopters by examining different traits related to innovation adoption. Moreover, this dichotomy was tested to influence an individual's willingness to pay for innovation. The first method was based on self-report items revealing an individual's passive innovation resistance. Before this research, this method was solely conceptualized as a confirmatory construct to determine indicators of PIR. However, throughout this research it has proven to be an applicable item scale in constructing subgroups with similar patterns of PIR. The second method was a new explorative method based on peer-prediction questions. This method was based on the idea that higher and lower predictions could potentially reveal an individual's preference towards innovation. Due to the fact that previous researchers included peer-prediction constructs within their methods, to elicit the truth or reveal preferences, there was a window of opportunity. This included an opportunity to construct a method based solely on peer-prediction questions. This method could indicate if individuals belonged to a particular cluster based on their answer pattern compared to that of others.

6.1 Self-report method measuring PIR

Replicating the confirmatory factor analysis and performing the latent class analysis on the 18 item scale of PIR provided new insights on how these items relate to each other. To begin with, it turned out that not all the factor loadings on the 18 item scale of PIR showed similar findings to the factor loadings found by Handrich and Heidenreich (2015). As a matter of fact, two items on cognitive rigidity showed negative loadings and one item on routine seeking behaviour did not pass the 0.5 threshold. While in previous research all these factor loadings were measured to be around 0.85. However, the item on routine seeking behaviour does not seem to deviate that much from previous research. In fact, a similar pattern can be recognized where this item scored on average 0.2 lower compared to the other factor loadings in both analysis. Furthermore, the negative loadings seem in line with my expectations with regard to how these items are formulated. Intuitively, the items on cognitive rigidity seem to contradict each other. However, Handrich and Heidenreich (2015) presented all the three items to be positive and well above the 0.5 threshold. Admittedly, they performed a more extensive study on this topic with more repeated measures and a larger number of observations, which in this case makes their findings more reliable.

Subsequently, latent class analysis performed on the 18 item scale did not show a clear separation in only high marginal means for the late adopters and low marginal means for the early adopters. Nevertheless, this dichotomy in items is mostly corroborated by the classification of these items to their main construct influencing PIR. The first 12 items belong to the construct of IRC, whereas the last 6 items belong to the SQS construct. In this case the pivot point takes place at eleventh item. This seems in line with Handrich and Heidenreich (2015) who tested the IRC construct to explain more variation in PIR compared to the SQS construct. Ultimately, it is interesting to see that this dichotomy in constructs naturally occurs when the LCA is performed and that scores on the IRC items are valued higher than the SQS items.

In addition, I compared the means on the 18 items scale of PIR based on the clustering of the peer-prediction method. It seems that these means also show a pivot point at the eleventh item. However, a new finding is that the items on SQSP show higher means for the early adopters in both the method. This is a surprising finding as SQSP is argued to contribute to innovation resistance.

6.2 Peer-prediction method measuring ICI

Not only the self-report method but also the peer-prediction method was analyzed by searching for patterns in the answer distributions and performing the LCA. To begin with, the histograms provided a recognizable pattern of a dichotomy in high and low predictions for most of the questions. With the exception of the question on the usage of virtual home assistants. On this question approximately 75 percent of the respondents reported predictions below 50 percent, which is low compared to the other questions. A possible explanation for these low predictions could be that respondents experience some privacy concerns with such voice controlled home devices. This could be due to the fact that people are unsure about how their personal data is dealt with and by who (Van Zoonen, 2017).

Furthermore, a paired t-test showed that questions on disruptive and incremental innovations did not significantly differ from each other. However, the one-sided t-test showed a marginally significant result that the answers on the disruptive question where higher than the incremental ones. Furthermore, this might indicate that questions on disruptive topics reveal more extreme answers. This could be related to the findings of Laukkanen et al. (2008) which stated that higher degrees of PIR were evoked by disruptive innovation compared to incremental ones.

Next, the LCA was performed to classify the respondents into early- and late adopters based on their peer-predictions. For the respondents classified as early adopters, all the mean predictions on the questions were higher compared to the predictions of the individual's classified as late adopters. Except for the question on the 3D printed organs. In addition, this question also provided the highest standard errors which made this question less reliable. This contradictory finding indicates that people normally more inclined to adopt faster than others, are less inclined to do so for this health innovation. Or the opposite, people less inclined to adopt innovation fast are more inclined to adopt this particular innovation faster. In regard to the topic of this question, allowing 3D printed organs into your body might be more an ethical issue than a determinant of innate innovativeness. This is reinforced by Peluso (2015) who studied adoption behaviour related to more ethically controversial innovations. He found that measures on moral norms and ethical self-identity influence the adoption behaviour for such innovations. Therefore, there might be an external factor influencing the answers on the 3D printed organs to be different.

6.3 Answering the hypothesis

With the additional findings on both the methods discussed, the answers to the hypotheses and research question can be formulated. Firstly, I argued the distribution of clustered early and late adopters based on the different methods to differ. Based on the findings of Bruner and Kramer (2007) who found only half of the respondents to experience both low PIR and high INI. Hereby, the following hypothesis was formulated:

H1: The clustered early and late adopters based on the self-report method and the peer-prediction method will not consist of entirely the same respondents.

The results on the chi-square test showed the clusters based on the different methods to be significantly dependent on each other. In addition, the Spearman correlation showed a significant negative correlation. Combining these results, a significant pattern is recognized where belonging to the early adopters based on one method is related to belonging to the late adopters based on the other method. In other words, these findings confirm my beliefs that the early and late adopters based on the different methods indeed divided most of the respondents into different groups.

Secondly, based on previous research including peer-predictions in methods to elicit to truth when no proxy is given (Prelec et al., 2017) or to reveal people's preferences (Baillon, 2017). Contributed by what psychologists describe as the false consensus effect (Ross et al., 1977). I believed a method solely based on the peer-prediction part could reveal an individual's innate innovativeness. In addition, I expected the clustering based on this method to work better in explaining the WTP than a method based on self-reported behavioural traits as these often show flawed results (Dunning et al., 2004). Moreover, people tend to overestimate their own positive traits and more accurately estimate traits of others (Epley & Dunning, 2000). Hereby I formulated the following hypothesis:

H2: The clustering based on the peer-prediction method can better explain the willingness to pay for innovation than the clustering based on the self-report method.

The results on the multiple linear regressions contradict this hypothesis and indicate the opposite to be true. Only the self-report method on PIR provided a clustering which marginally significantly affected the WTP to go up or down depending on being an early or late adopter. For the peer-prediction method, the use of this particular questions on prospective adoption behaviour of others did not provide a clear pattern of early and late adopters that influences the WTP. Finally, by combining the results of these hypothesis, the following research question can now be answered:

Can actual innovation adoption behaviour better be elicited by clustered early and late adapters based on self-reported behavioural traits related to resistance or peer-prediction of innovation adoption?

Actual innovation adoption can be better elicited by clustered early and late adopters based on the self-reported behavioural traits related to resistance. The results indicate that early adopters based on their low resistance towards innovation tend to pay more for an innovation, whereas late adopters based on their high resistance tend to pay less for an innovation. It seems reasonable that people who are less resistant towards innovation are also inclined to pay more. This higher price might also justify for the use of the adopter categories as clusters. As a higher price could also indicate that people want to buy it sooner. People with more resistance are less likely to buy to innovation, or at least at a lower price, indicating that they most likely will not buy it or maybe later in time. Hereby, price setting of new innovations might indirectly segment your customers. These findings, suggest that using the 18 item scale of PIR has potential to identify customer profiles more accurately on unobserved resistance that influences the choice to adopt innovations.

7. Limitations and recommendations

First, the discussion on the peer-prediction method has already shown that the answer distributions of the prediction questions could be related to matters of privacy, ethics or potentially the distinction between incremental and disruptive innovations. Due to the high variation chosen in the topics and the limited amount of questions, the peer-prediction method might not have had the best chance of revealing preference for innovation. With only 3 questions on incremental innovations and 3 questions on disruptive innovations, the method was very limited. Potentially, in future research I recommend innovation preferences to be divided into measuring people's preference towards the latest new gadgets (Bruner & Kumar, 2007), or the perception of disruptive innovations (Christensen, Raynor & McDonald, 2015). In addition, it also seems relevant to account for privacy sensitivity related to these innovations (Van Zoonen, 2016), or how morally controversial these innovations are (Peluso, 2015) when measuring adoption behaviour.

Second, a reason that the clustering based on the peer-prediction method did not provide significant results on the WTP might be due to the number of questions and the formulation of the questions. Compared to the self-report method, the peer-prediction method consisted of only one third of the number of items the self-report method had to perform the LCA on. A study by Wurpts and Geiser (2014) demonstrated that more items, in combination with a larger sample size, and higher quality items led to more proper classifications when using LCA. A particular interesting finding was that a smaller sample size could sometimes be compensated by the inclusion of higher quality items. Hereby, the quality of the items on the peer-prediction method could be increased by framing the questions better. In the current formulation of the questions a clear definition of ‘people’ is missing. By this means, the questions were open to own interpretations of at what level ‘people’ was meant. In example, it could be people in your near surroundings, the people in the Netherlands, the people living in the Western world, or even people worldwide. All these different interpretations will lead to different predictions, which makes these items of lesser quality. Adding the description ‘people like you’ in the questions could be a way to establish more overestimation of others sharing similar beliefs as people are directly told to think about themselves. Therefore, I recommend other researchers to include more items and to formulate these items as clear as possible. Hence, this can increase the quality of the indicators and thereby the use of LCA.

Third**,** the peer-prediction method is solely based on product related questions whereas in the self-report method only the 3 items on SQSP are dedicated to products. This made it interesting to explore how the questions on SQSP were answered within the clustering based on the peer-prediction method. I found a prevalence of higher means on the SQSP items for respondents classified as early adopters compared to late adopters in both the methods. This suggests that early adopters are more satisfied with products than late adopters. This seems surprising as previous researchers argue higher SQSP to result in more innovation resistance (Bagozzi & Lee, 1999). Future researchers could study the effect of SQSP even further and especially how it influences consumer behaviour in terms of innovation adoption. Intuitively, it seems reasonable that if an individual is satisfied with current products, this same person would also appreciate the benefits of new innovations. However, if this is not the case than question on products might not have been the best choice to test for the peer-prediction method.

Fourth, the concept of innate consumer innovativeness might not be fully captured by the way it was operationalized. The new method was constructed to explore if the usage of solely peer-prediction questions would work to reveal an individual's’ innovativeness. Therefore, only these prediction questions were used to proxy the innate innovativeness. To begin with, it seems reasonable that high predictions on innovations reveals some characteristics of novelty seeking behaviour. Consisting of exploring new things, or buying innovations quicker/more frequent (Hirunyawipada and Paswan, 2006). However, the main emphasis of the prediction questions remains on beliefs on what others will do. If we want to measure an individual's innate consumer innovativeness more accurately, it could be relevant to conceptualize an item scale relatable to the one on PIR. By capturing ICI in a multiple dimensional construct, this item scale could potentially give a better proxy of an individual's actual innate innovativeness and its relationship with the WTP for innovation.

Fifth, in this thesis a very clear construct is followed, where the self-report method on PIR is compared to the peer-prediction method on ICI. This makes it impossible to directly compare if ICI or PIR influences WTP better. The same counts for comparing both the methods to each other. As previously discussed above the current explorative peer-prediction method faced some limitations. If the emphasis of this thesis would be shifted towards comparing the methods, the methods should measure to same construct. We found an indication that the answers to the 18 item scale of PIR can provide a clustering that influences the WTP for innovation. Future researchers could transform the 18 item scale statements into statements on peers. They could conduct an experiment where half of the respondents report on statements on their own beliefs, and the other half on the same statements on peer beliefs. In this way, a fair comparison can be made if the peer-prediction method works or not.

Sixth, to create a proxy for the actual adoption behaviour of the respondents the BDM method was used. The main advantage of the usage of the BDM method is the ease at which respondents understand the method (Brebner & Sonnemans, 2018). However, my implementation of the BDM method differed from the most standard format. The BDM method was presented in the form of a multiple price list (MPL), instead of a single measurement. Including, the MPL added simplicity to the construct as there could be no misunderstanding on the options provided per price. Nevertheless, with a single measurement the valuation of the innovation could have been measured more precise. Furthermore, the construct at which only one respondent could actually buy the innovation had to be added to the explanation of the method. This additional description might made it harder to understand in one go, but resulted in a more deliberate answer. In addition, the win rate was quite low: 1 out of 81, approximately 1.2%. Voelckner (2006) compared a sample where all the respondents had to make their purchase decision for real, to a sample where only 10% of the respondents had to. Hereby, no significant difference in the respondent's WTP between the two groups was found. By way of contrast, these findings cannot be extrapolated to my survey design with a 1.2% chance, as it is unclear what the consequences of this lower chance of making the purchase decision for real will be on the reported WTP. Therefore, I recommend future researchers to choose a rate of at least 10% to be sure that the WTP is not significantly affected.

Seventh, for the BDM method to work an actual innovation had to be chosen. In this survey I presented a Wake-up Light, which the respondents could adopt by filling in the MPL per euro. This method, including this particular innovation, was chosen as respondents had to make a real and incentivized decision, making it an economic experiment. Hereby, the Wake-up Light was chosen as this innovation is not accompanied by any known societal implications of privacy or ethics. However, it can be argued that a Wake-up Light is not the newest innovation available on the market. Moreover, when making a distinction between early and late adopters, preferably an innovation is chosen which people do not already possess. In contrast, my design does not account for respondents that report a low WTP for the Wake-up Light, because they already own the product. In that case these respondents should actually report the highest WTP as they actually adopted the innovation. To account for this, future researchers could experiment with selecting innovations offered at Kickstarter.com, as these products only go into production if they get enough funding, making it impossible for respondents to obtain the innovation beforehand.

Lastly, Rogers (2003) constructed the adopter categories based on 5 categories, whereas in this research the respondents are only divided into two aggregated categories of either early or late adopters. Since the sample size was considerably small the dichotomy or early and late adopter by Kim et al. (2010) was chosen. However, in real life not everybody can be classified as either an early or a late adopter. Here, some people will belong to the vast majority, whereas others belong to the most extreme observed adoption behaviours. Interestingly, when the robustness check with the cluster including 3 categories was applied to the current findings on the 18 item scale of PIR it seemed to provide an even more significant effect on the WTP. Hence, applying multiple adopter categories will provide more precise effects belonging to the different groups. Therefore, future research could further explore the effect of using all the adopter categories when classifying the respondents on their behaviour towards innovation.

Overall, this thesis provided new insights on peer-predicted adoption behaviour on different incremental and disruptive innovations. Unfortunately, the clustering based on the answer distributions of this peer-prediction method did not provide a significant change in the WTP for innovation. This was possibly due to the framing of the questions, which could be improved by future research on this topic. In contrast, the self-report method on the 18 item scale of PIR, marginally significantly indicates that being clustered as an early (late) adopter causes the WTP to increase (decrease). These findings create new opportunities for researchers in the area of innovation adoption. The 18 item scale of PIR could be used in practical situations of predicting adoption behaviour based on self-report traits related to resistance. In addition, the 18 items could be transformed into peer-report traits to test if peer-predictions provide different answer distributions.

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Appendix

Survey questions Self-report method on 18 item scale of PIR

Below there are 18 statements on your own behaviour. Please fill in to what extent you can relate to these statements, where the answers possibilities range from completely disagree (-) to completely agree (+).

	Completely disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Completely agree
I generally consider changes to be a negative thing.	○	○	○	○	○	○	○
I like to do the same old things rather than try new different ones.	○	○	○	○	○	○	○
I'd rather be bored than surprised.	○	○	○	○	○	○	○
If I were to be informed that there's going to be a significant change regarding the way things are done at work, I would probably feel stressed.	○	○	○	○	○	○	○
When I am informed of a change of plans, I tense a bit up.	○	○	○	○	○	○	○
When things don't go according to plans, it stresses me out.	○	○	○	○	○	○	○
Often, I feel a bit uncomfortable even about changes that may potentially improve my life.	○	○	○	○	○	○	○
When someone pressures me to change something, I tend to resist it even if I think the change may ultimately benefit me.	○	○	○	○	○	○	○
I sometimes find myself avoiding changes that I know will be good for me.	○	○	○	○	○	○	○
I often change my mind.	○	○	○	○	○	○	○
I don't change my mind easily.	○	○	○	○	○	○	○
My views are very consistent over time.	○	○	○	○	○	○	○
Overall, my personal need for innovations in the field of technological products has been by far not covered in the past.	○	○	○	○	○	○	○
Overall, I consider the number of innovations in the field of technological products as being too low.	○	○	○	○	○	○	○
Overall, I consider the pace of innovations in the field of technological products as being too low.	○	○	○	○	○	○	○
In the past, I was very satisfied with available technological products.	○	○	○	○	○	○	○
In my opinion, past technological products were completely satisfactory so far.	○	○	○	○	○	○	○
Past technological products fully met my requirements.	○	○	○	○	○	○	○

Survey questions Prediction method on ICI

Below there are six prediction questions on the adaption behavior of others. Give your most accurate prediction on a scale ranging from 0 till 100 percent reflecting your own beliefs on what others will do.

0	10	20	30	40	50	60	70	80	90	100

What percentage of people do you predict to acquire the latest new smartphone at least once every two years?

What percentage of people would allow 3D printed organs or other human parts into their body if necessary?

What percentage of households will use a virtual home assistant in 5 years from now?

By 2025, artificial intelligence (computers/robots) could take over approximately half of the current workforce (human jobs), what percentage of people would allow for this to happen?

What percentage of people will use biosensors and trackers in everyday life within 5 years from now?(Biosensors are technology-enabled activity trackers into clothing or accessories which allows consumers and doctors to easily monitor health.)

Imagine cultured meat becomes available in 2025 at the same price as regular meat, what percentage of people would actually move towards eating this lab-grown meat? (cultured meat is created by painlessly harvesting muscle cells from a living animal and nurture these cells so they multiply to create muscle tissue).

Survey questions BDM method on WTP

Consider the following innovation: The Wake-up Light (worth around €25). The Wake-up Light is an alarm clock that simulates the sunrise (or sunset) to wake people up more gradually which will enhance their energy level in the morning. The Light has the following features: snooze function, digital FM radio, 6 different nature sounds, mood light function with 6 colors and 10 adjustable levels of light brightness.

One participant, randomly selected, will get €25. If you are this participant, you can decide to use part of the money to buy the Wake-up Light from me. The list below asks you whether you would buy it for various prices. Take your time and evaluate the options with care because your decision may be carried out for real.
This will work as follows: imagine you are the randomly selected participant; the computer will then draw at random a price for the Wake-up light between 1 and 25 euro. I will look at your decision for this price in the list below. If you choose not to buy the Wake-up Light then you keep the €25. If you buy the Wake-up Light, you will receive it, plus the remaining money.

NOTE: Fill in the option to buy/don't buy for all the prices presented below.

	I Buy and get the product	I don't Buy and receive €25
€1 (you pay €1, keep €24)	○	○
€2 (you pay €2, keep €23)	○	○
€3 (you pay €3, keep €22)	○	○
€4 (you pay €4, keep €21)	○	○
€5 (you pay €5, keep €20)	○	○
€6 (you pay €6, keep €19)	○	○
€7 (you pay €7, keep €18)	○	○
€8 (you pay €8, keep €17)	○	○
€9 (you pay €9, keep €16)	○	○
€10 (you pay €10, keep €15)	○	○
€11 (you pay €11, keep €14)	○	○
€12 (you pay €12, keep €13)	○	○
€12 (you pay €12, keep €13)	○	○
€13 (you pay €13, keep €12)	○	○
€14 (you pay €14, keep €11)	○	○
€15 (you pay €15, keep €10)	○	○
€16 (you pay €16, keep €9)	○	○
€17 (you pay €17, keep €8)	○	○
€18 (you pay €18, keep €7)	○	○
€19 (you pay €19, keep €6)	○	○
€20 (you pay €20, keep €5)	○	○
€21 (you pay €21, keep €4)	○	○
€22 (you pay €22, keep €3)	○	○
€23 (you pay €23, keep €2)	○	○
€24 (you pay €24, keep €1)	○	○
€25 (you pay €25, keep €0)	○	○

Confirmatory factor analysis per dimension of PIR replicated in Stata