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Perceived technology clusters and ownership of related technologies:

the case of consumer electronics

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Perceived technology clusters and ownership of related technologies: the case of consumer electronics

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Abstract

We contribute to the understanding of how technologies may be perceived to be part of technology clusters. The value added of the paper is both at a theoretical and empirical level. We add to the theoretical understanding of technology clusters by distinguishing between clusters in perceptions and clusters in ownership and by proposing a mechanism to explain the existence of clusters. Our empirical analysis combines qualitative and quantitative methods to investigate clusters of consumer electronics for a sample of Dutch consumers. We find that perceived clusters in consumer electronics are mostly determined by functional linkages and that perceived technology clusters are good predictors of ownership clusters, but only for less widely diffused products.

Introduction

In his famous book on the diffusion of innovations Rogers (2003, p.249) states that: "Innovations are often not viewed singularly by individuals, but they may be perceived as an interrelated bundle of new ideas. The adoption of one idea may trigger the adoption of others." This intuition has been taken up by a few researchers that have further developed the seminal idea of perceived related technologies to the concept of *technology clusters* and have tested it in practice[1]. The word *technology* has been used to refer to technology-based innovations, and has most often been applied in the field of information technologies. While the claim in Rogers (2003) implicitly assumes that an innovation entails a new idea, technology clusters specifically refer to new ideas embodied in actual products.

The motivation for an interest in technology clusters has been spurred by the empirical evidence that such clusters can be significant predictors of the adoption of innovations (see for instance Lin, 1998 and Busselle et al., 1999). They have, for example, been defined by shared infrastructures (LaRose and Atkin, 1992), or by brand (Warlop et al., 2005). Clusters have also been determined in relation to the lifestyle of the adopter (Ettema, 1984), or to some emotional attachment (Kwortnik Jr. and Ross Jr., 2007).

In this paper we propose that the literature on technology clusters can make further steps in two main directions. First, as discussed in Vishwanath and Chen (2006),

[1] Some authors prefer the term *innovation clusters* (see LaRose and Hoag, 1996 and Neuendorf, Atkin and Jeffres, 1998). Both terms are in fact also used in the literature on industrial clusters for clusters of technology/innovation-oriented firms.

technology clusters have been used and defined in *ad hoc* ways depending on the focus of the study. The definition proposed by Rogers implies that there is a relationship between two different types of clusters, namely that a perceived relationship between products (perceived clustering) is predictive for the combined ownership of these products (ownership clustering).

Perceived relationships among products are the focus of product categorization literature (see for instance: Nedungadi et al., 2001 and Rosa and Porac, 2002), while the combined ownership of technologies is discussed in the technology adoption literature (Leung and Wei, 1999 and Vishwanath, 2005). Most studies consider technology clusters as exogenous and do not aspire at formulating a theoretical mechanism that explains their existence.[2] Mechanisms on how clusters come to exist can be formulated both for perceived technology clusters and for the combined ownership of technologies. The theoretical mechanism behind both perceived and ownership clusters is bound to depend on the specific technologies considered. We propose a theoretical mechanism for both types of clusters and we relate them by testing whether perceived clusters are a good predictor of actual ownership. Continuing the line of most previous studies on this topic, we apply our theory on information related consumer electronic products.

Second, Vishwanath and Chen (2006) have suggested that different types of adopters may perceive technology clusters differently. They find that early-adopters perceive technologies to be related through functional interdependencies and a shared infrastructure, while non-adopters relate technologies based upon their functional merits. Their contribution is a first step towards a better understanding of the individual characteristics of adopters that shape technology clusters. In this paper we analyze the role of consumers' prior knowledge on the likelihood of linking two technologies together.

In the next section we develop a theoretical framework for technology clusters in consumer electronics. Next, we test our hypotheses on a sample of Dutch consumers using a combination of qualitative and quantitative research methods. In the conclusions we discuss the implications of our results for the literature on technology clusters and suggest some managerial implications as well.

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[2] The studies by LaRose and Atkin (1992) and Vishwanath and Chen (2006) are the only two exceptions that we are aware of.

Theoretical framework

Technology clusters in consumer electronics

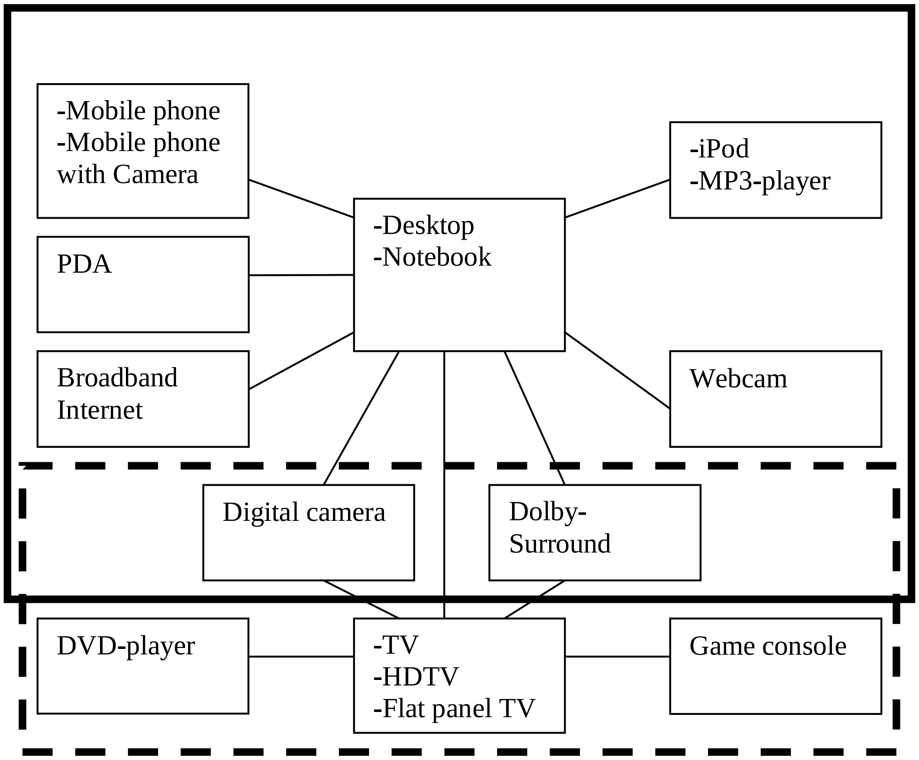

Figure 1: The 16 technologies and their shared infrastructure. PDA (Personal Digital Assistant) HDTV (High Definition TV, iPod, Flat panel TV, Game console, Webcam, MP3-player, Notebook (or laptop),, Dolby-surround, Mobile Phone with camera, Digital camera, Broadband Internet, Desktop, DVD-player, Mobile Phone, TV.

Following Rogers (2003) a technological innovation[3] can be defined as a technology/product that is perceived to be new by an individual. This innovation can be viewed as being stand-alone or as being part of a perceived larger whole, a technology cluster (LaRose and Hoag, 1996, Rogers, 2003; Vishwanath and Chen, 2006).

Figure 1 graphically displays 16 different technologies[4] that are considered in this study. The underlying *infrastructure* is also depicted. The lines that connect the technologies display possible physical connections, like cables or Bluetooth, between them. The hubs in the infrastructure can be considered “base technologies”: they are standalone equipments to which other devices can be linked so that the performance of either of the two devices increases. For consumer electronics two base technologies

[3] In what follows we shall simply refer to *innovations* and use the term interchangeably with new products and new technologies.
[4] The products chosen cover a wide range in terms of diffusion (from TV to PDA). We sought for a relatively complete list of consumer electronics while at the same time limiting the number of products to 16 in order to keep the response rate of our questionnaire high.

can be identified, the PC and the TV. The PC is represented by the desktop and the notebook, which have similar functions and can be considered to a great extent as *functional substitutes*. Together with ordinary television, we consider two functional substitutes, HDTV and FPTV. All other technologies are considered "peripheral". Peripheral technologies are *functional complements* of the respective base technologies. This complementarity entails a strong linkage between peripheral and base technologies since the proper functioning of peripheral technologies is contingent upon the ownership of the corresponding base technology.

Perceived clusters in consumer electronics

According to Rosa and Porac (2002) the categorization of products by individuals depends on how the products are experienced, which in turn largely depends on contextual factors. Yeh and Barsalou (2006) propose a general classification of properties on which cognitive categories can be based. Their classification can be used to understand which properties define categories of products in consumer electronics. They distinguish among categories based on *entity properties* (e.g. small phones, thin TVs), *situational properties* that describe the physical setting or event to which the product is associated (e.g. conversing, hearing ring tone and beeps for the mobile phone), *taxonomic properties* (neighbouring concepts in a cognitive taxonomy like music devices) and *introspective properties*, which describe agents subjective perspective on the target object (e.g. annoying devices, convenient products). Products sharing common properties fall into the same perceived category.
Following the representation in Figure 1, we consider categories of products based on linkages defined by functions, an example of categorization based on taxonomic properties. We define four different categories of linkages and corresponding indicators of 'infrastructural distance' between technologies.

1. Overlapping functions (OF): technologies perform the same basic function, in other words, they are functional substitutes. For example, a notebook basically does the same as a desktop computer. The infrastructural distance between the technologies is zero.
2. Functional interdependencies (FI): the technologies are directly connected to each other and the performance of either technology depends on this connection, they are functional complements. For example, broadband internet does not function without a computer. The infrastructural distance between the technologies is one.
3. Shared base technology (SBT): the technologies are connected with each other through a base technology. A webcam for example is connected to the internet through a computer. The infrastructural distance between the technologies is two.
4. Unknown (Unk): This category entails all other linkages, which cannot be related to a functional linkage, but relate instead to entity, situational or introspective properties (such as lifestyle- or brand-related properties). The distance between the technologies is three or greater.

The table in Appendix 1 shows how we classified each of the possible 120 links among the 16 technologies[5]. The classification stems directly from Figure 1 and from

[5] $(16^2 - 16)/2 = 120$

the four categories defined above: functional substitutes are classified as ‘OL’, while functional complements as ‘FI’.
Given the existence of clear base technologies in the case of consumer electronics, we suggest that linkages based on infrastructural distance will be significant predictors for perceived technology clusters. Specifically, we assume that a lower infrastructural distance is associated with a higher likelihood for perceiving technologies as part of the same cluster. This implies two main claims. First, products with overlapping functions (substitutes) are most likely to be perceived as being part of the same cluster. Second, factors different from functional linkages, falling in our ‘Unknown category’, matter the least for predicting clusters in consumer electronics. Our first hypothesis is then:

Hypothesis 1: The larger the infrastructural distance between two technologies, the smaller the likelihood of perceived linking between them.

Prior knowledge and perceived technology clusters

As discussed in the introduction, Viswanath and Chen (2006) found that adopters and non-adopters perceive relationships among technologies differently. Early adopters relate technologies based on their functional interdependence, while later adopters focus more on overlapping functions. These findings are in line with the Consumer Learning by Analogy model (CLA) (Gregan-Paxton and Roedder John, 1997). The theory considers experts as individuals with a larger prior knowledge and claims that experts perceive technologies to be related based on actual relationships or “links”, like a shared infrastructure. Instead, non-experts perceive technologies to be related based on single attributes (like having overlapping functions). This also implies that non experts use more entity properties and introspective properties than experts. Furthermore, Moreau et al (2001) found that categorization for really new products depends on external cues (situational properties, entity properties, but certainly not taxonomic concepts), because there is no existing knowledge base to fit them in. The knowledge base determines the extent to which an individual makes use of taxonomic concepts in associating concepts. In assessing technology clusters the level of expertise and thus the knowledge base can play an important moderating role on the type of link used to relate technologies. We propose the following hypothesis:

Hypothesis 2: Individuals with a large knowledge base about the products are more likely to perceive links based on functional interdependence, while individuals with a low knowledge base are more likely to perceive links based on overlapping functions.

Perceived clusters and actual ownership clusters

The relationship between perceived linking of technologies and actual ownership forms the basis of Rogers (2003) argument on technology clusters. His starting assumption is that perceived clustering can enhance the likelihood of adoption. Logically, consumers will only purchase technologies that they can actually put to use. If one does not posses or has no access to a television, it is of little value to purchase a DVD-player (for own use). This means that ownership patterns are

expected to follow the patterns laid out by the shared infrastructure. In the case of functional interdependencies clustering does favour adoption, but this is most likely when the performance of the base technology gets enhanced by the peripheral technology. If two different products have the same function, a consumer does not need to aspire to own both products. An example is the case of the iPod and an ordinary MP3 player. Since both play digital music, there is little reason for an individual consumer to own both products, except for a replacement purchase. Finally, the likelihood of adoption as a result of clustering decreases if there is only a shared base technology, and the peripheral technology has no added value from the other technologies.
Based on the above considerations, we expect the type of link to explain the difference between perceived clusters and observed ownership patterns. From this it follows that:

Hypothesis 3: The relationship between perceived technological clusters and actual technology ownership is moderated by the type of link in such a manner that links based on functional interdependencies and a shared base technology have a higher likelihood of being found in ownership clusters than links based on overlapping functions.

We expect no effect of knowledge base in actual ownership patterns, because we view the knowledge base as the combined ownership of technologies: this means that the knowledge base is incorporated in our dependent variable.
We add a last but very important control factor to our model. In modelling perceived relationships we are only dependent on the preferences of the respondents. This is not the case for patterns in ownership; here diffusion of the technology through the population also plays a significant role. In testing our hypotheses we would like to test whether the actual patterns in ownership depart significantly from what we would expect to find on the basis of chance. However, in the case of two widely diffused technologies (the added percentages of ownership of both technologies is larger than 100 %) links will be formed not only by chance, but also because it is practically certain that both technologies are owned by a given consumer. The amount of diffusion thus heavily influences our results. In our methodology we discuss how we deal with this issue.

Empirical analysis

As concerns our empirical analysis, we will combine the results of oral interviews with survey data. Most contributions in this field come from survey data (e.g. LaRose and Atkin (1992), LaRose and Hoag (1996), Leung and Wei (1999), Vishwanath and Goldhaber (2003)). A notable exception is the paper by Vishwanath and Chen (2006), who take an original approach by using multi-dimensional scaling techniques.

To test our hypotheses two studies were conducted.

- A study with semi-structured interviews combining a qualitative analysis to investigate how consumers perceive technology clusters and a statistical analysis to test hypotheses 1 and 2.
- A quantitative study to find out which technologies are actually owned in combination with each other and to compare them with the perceived clusters. This study seeks to confirm hypothesis 3.

Study one: A study into perceived clusters

Methods

Sample and data collection

A group of 21 university students of a research methodology course conducted a series of 47 interviews among a sample of consumers. Although the sample size is too small to form an adequate representation of the population, quota by age and sex were used to ensure a broad sample[6]. All interviews were held in the respondents own houses. The interviews were recorded on audio and written out literally afterwards. At the beginning of the interview, the interviewer laid out in front of the respondent a series of 16 cards with the names and pictures of the previously mentioned 16 technologies. The cards were laid out in a predetermined format of two horizontal rows consisting of eight cards. The interviewer asked the respondents whether they would group the cards into, for them, logical clusters. To prevent influence through external cues (Moreau et al, 2001), no hint for the manner of clustering (such as hints for a category structure (Negungadi et al. 2001)) was given prior to this question. It was told that if respondents required a technology more than once to form a cluster, they could receive a spare card. After the respondent had finished laying out the combinations, the interviewer wrote these down. Next the interviewer asked for each cluster, why the respondents had made this particular combination of technologies. After giving these reasons, the respondents were asked which of the technologies they actually owned.

Analysis

Per respondent all cluster data was put into a 16 by 16 matrix, where the rows and columns stand for the 16 technologies; there were 120 different possible relations. The cells represent the count of the number of times that the technologies were related to each other in the interviews.

All relations were coded in the manner based on our theory (see appendix 1): (1) the products have overlapping functions, (2) the products are functional interdependent, (3) the products share the same base technology, (4) unknown.

There are two levels at which we can analyse our data: we can analyse the aggregated matrices of the entire sample, or we can analyse the matrix of each respondent separately. This implies a two-level model (Snijders and Bosker, 1999), with the possible combinations at the macro-level and each respondent at the micro-level. In this case we prefer a two-level approach, because it allows us to estimate the effect of the knowledge base variable, which is on the micro level. We measure knowledge base (KB) by the total number of products actually owned, a proxy for the objective knowledge base.

From the tables we constructed a vector with values zero and one for all possible combinations of technologies for all respondents: the vector consisted of 5640

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[6] The study by Vishwanath and Chen (2006) only addressed young consumers. Our sample is representative for all ages and thus deals with one of the further tests indicated by the two authors in their conclusions.

observations. First, to determine which combinations (if any) were perceived as clusters we fitted a binomial random effects model with an intercept dependent on the respondent, using the lme4 package (Bates and Sarkar, 2006) of the R-program (R-development core team, 2007). As dependent variable we used the dummy vector with the links made by all respondents, the independent variable was a factor variable, containing all 120 possible combinations.
Next, to test hypothesis 1, we estimated a binomial random effects model with an intercept dependent on the respondent. The model predicts the probability of each perceived link by the respondents. The independent variable is a factor capturing the four types of functional linkages in order of increasing infrastructural distance (overlapping function is the reference category corresponding to a zero distance).
To estimate the moderating effect of hypothesis 2, we added interaction terms between the factor capturing functional linkages and the knowledge base of consumers (KB). In order to determine the effect of knowledge base for each type of link, we also inserted the knowledge base variable in four separate models where the dependent variable relates to perceived links based on the four types of links.
To find evidence for our theoretical arguments about perceived clusters, we analysed the interview question with respect to the motives used by respondents to form their clusters. This was done by interpreting and coding the text fragments of the answers with simple labels for each type of link. This is a way of testing whether our theoretical explanations about the reasons for clustering were correct. The coding was checked for inter-subjectivity to ensure a correct interpretation of the text. We thus have four labels, one for each type of link. In analyzing the interviews we found however that the arguments for linking were often a mixture of the labels. In those cases all relevant labels were attached to the text fragment. The number of times a certain label was mentioned is an indicator for the validity of our results (Baarda et al, 2005).

Results

Statistical analysis

Appendix 2 presents the results of the analysis aimed at identifying the clusters perceived by the respondents. To ease interpretation, we show the actual number of times the respondents clustered the technologies together, but the asterisks indicate the p-values resulting from the analysis. The significant values indicate that the likelihood that the two technologies are perceived to be linked significantly departs from what is expected on the basis of chance alone. Establishing clusters has a high degree of arbitrariness. We have chosen to look at all links above a threshold value that gives a relatively coherent pattern, in this case this was 21 links. This has no further consequence for the rest of the analysis which will take into account all links at the individual level. The sole purpose here is to see whether technology clusters can actually be discovered. From appendix 2 we can distinguish relatively coherent patterns of clusters if we look at the links that are mentioned more than 21 times (see table 1), only the position of the PDA is somewhat ambiguous, because it ends up being in two clusters.

Cluster	Technologies
1	TV, HDTV, FPTV, DVD-player, Dolby surround
2	Desktop, Laptop, Broadband Internet, Webcam, Game consul, PDA
3	Mobile Phone, Mobile Phone with Camera, Digital Camera, PDA
4	MP3-player, iPod

Table 1: The clusters that can be found from appendix 2 based on 21 perceived links or more.

Y=Prob (Perceived link)	All types	Interaction model	OF	FI	SBT	Unk
Intercept	0.158	-0.969**	-1.020**	-1.556***	-2.231***	-2.729***
OL						
FI	-0.673***	-0.601**				
SBT	-1.384***	-1.243***				
Unk	-2.630***	-1.735***				
KB		0.137***	0.145***	0.124***	0.115**	0.014
FI* KB		-0.010				
SBT * KB		-0.018				
Unk * KB		-0.104***				
AIC	5195	5180	907	1719	1035	1527
Number of respondents	47	47	47	47	47	47
Number of observations	5640	5640	705	1363	987	2585

Table 2: The results of the random effect models predicting the likelihood of perceived links.
***: $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2 presents the estimates of the random effects models that test hypotheses 1 and 2. Overlapping functions is the reference category and has therefore no estimate.

The model predicting the effect of the type of link on the likelihood of linking shows that the larger the distance between the technologies becomes, the smaller the likelihood of linking is. In other words, compared to linking based on overlapping functions, linking on the basis of functional interdependencies has a smaller likelihood, followed by linking based on shared base technologies and thereafter followed by the unknown type of linking. This confirms hypothesis 1 and implies two corollary results that are in line with our expectations. First, overlapping functions is the most important factor for consumers to perceive two products as similar. Second, the unknown category is the least important factor for predicting clusters, indicating that considerations not based on functional linkages, such as lifestyle or product attributes like brand, matter the least for perceived clusters in consumer electronics. We will see how the latter result is also confirmed by the findings from the qualitative analysis.

The model that adds the knowledge base and its interaction with the type of link (Interaction model) shows that there is a moderating effect between the unknown types of links and the knowledge base. In the last four columns we explore this interaction further, by using knowledge base as a direct predictor for the probability of linking for each of the four linking categories. This enables us to determine to which type of linking knowledge base is significantly related. It turns out that the knowledge base has a significant positive influence on the likelihood of linking on the basis of overlapping functions, functional interdependencies, and on the same base technology. There is no effect for the unknown types of linking. This indicates that whatever the size of the knowledge base, consumers do not differentiate much between types of links when clustering. What we can say is that people with a larger knowledge base make more links in general. This partly rejects hypothesis 2, as individuals with a large knowledge base do perceive clusters more based on functional interdependencies, but non-experts do not perceive clusters more on the basis of overlapping functions. The partial rejection of hypothesis 2 implies that in our design we did not succeed in confirming the theories of Gregan Paxton and Roeder John (1997), neither did we replicate the results of Vishwanath and Chen (2006). There can be several explanations for this. First, our sample size might have been too small; second, the way of relating the technologies may not sufficiently allowed to detect different types of linkages other than functional ones; third, the knowledge base of the respondents might not have been differentiated enough to detect any statistically significant differences.

The sample size limitation is probably not the main issue considering the fact that we had 120 observations for each respondent. The research design was focused at identifying clusters over all technologies, without any limitations to the size of the cluster. This is a difference with respect to Vishwanath and Chen (2006) who only researched pairs of technologies. Our study did not however instruct respondents on any number of possible linkages, neither on the types of linkages. Probably the respondents' desire for parsimony was stronger than their distinction between different types of links or other possible means to relate technologies. The range in knowledge base was large among the respondents. The set of technologies also contained some very new products next to more conventional products. The respondents were able to categorize these new products in a sensible way, based on the knowledge they already had from other products.

These considerations lead us to believe that the theoretical arguments elaborated for hypothesis 2 are still correct, and might be confirmed in the controlled situation of a laboratory experiment such as Vishwanath and Chen (2006) did. However the effects may be too subtle to be confirmed when transferred to a real-life context (Campbell and Stanley, 1966). If we had added an almost totally unknown product, a really new product or even a non-existing product to the set, we might have found different effects. This is however far from reality in our particular product domain, where most products are related functionally and therefore familiar to their users.

Qualitative analysis

The great majority of the text fragments of the respondents explaining their grouping indeed point to clustering based on functionality and infrastructure. Some illustrative examples (all translated from Dutch) follow below. The first one is from a 50 year old woman with moderate experience with consumer electronics. She describes her motivation for grouping the desktop, the laptop, broadband internet, the webcam and the PDA.

Interviewer: "*Could you tell me why you have made these groups?*"
Respondent: "*Yes, the computer and the laptop are computers of course*".

Interviewer: *"Is that your first group?"*
Respondent: *"That is my first group indeed. Broadband internet also belongs to that group. I wouldn't know were else to put it than with a computer. A webcam is also connected to a computer. Then I also have the personal digital assistant, which is a sort of computerized agenda, I believe."*

This example shows that the respondent started reasoning from overlapping functions (the laptop and the desktop computer) and then added other technologies to the cluster that can be connected the base technology. Another example comes from an inexperienced 76 year old male, who explains his motivation for clustering the desktop, the laptop, the game consul and the webcam:

Interviewer: *"Why did you put these items together into one group?"*
Respondent: *"This is a kind of computer?"* [Referring to the notebook]
Interviewer: *"Yes it is a kind of computer."*
Respondent: *"At least, I always see my son in law walking around with one. Well and this is a game computer. And a webcam, I don't now it, but you always hear that there is trouble with those things, with all of those dirty old men. You also connect those to a computer, don't you? So I thought, yes."*

We see the same pattern here. The respondent starts reasoning from overlapping functions (the desktop, the game consul and the laptop) and afterwards (via a step of irrelevant information) he also connects a device that is functionally dependent on a computer.

We have many more examples of this kind of reasoning. Most arguments for clustering contained a mixture of functional overlap and functional interdependencies. There were other sporadic arguments for clustering, like that it appealed to young people or because the items were gadgets. In general however the arguments from the interviews confirm our findings in the models. Of the 193 text fragments that were analysed, 165 referred to a mixture of overlapping functions and functional interdependencies and a shared base technology. Only 28 fragments referred to other arguments.

The results of the qualitative study show that the infrastructural distance between technologies is the most important determinant for linking two technologies. This is in line with the claims of LaRose and Atkin (1992). Alternative explanations like lifestyle are less prominent, clustering starts from functionality. This result is in line with the estimated effects associated with the 'Unknown' category in the statistical analysis.

To summarize the findings from study 1:

- The type of link predicts the likelihood of perceived clustering. The larger the infrastructural distance between two technologies, the smaller the likelihood of perceived linking between technologies becomes.
- Technology clusters are perceived mostly based on functional linkages, while perceived similarities among products based on other considerations are only marginally used.

- The larger the knowledge base the larger the likelihood of linking technologies based on overlapping functions, functional interdependencies and a shared base technology.

Finally, we would like to make a note on methodology. We believe that the motivations behind perceived clustering are better analyzed with qualitative research methods, while evaluating ownership clusters is better done with quantitative research. In our qualitative research we have recovered our theoretical framework in the answers given in the interview. These answers supported our theory and the theory predicted the clusters correctly. This makes the findings of study 1 reliable and a valid predictor for study 2.

Study 2: A quantitative survey about ownership clusters in consumer electronics

Methods

Sample and data collection

A survey was administered by students of an introductory research methodology course among consumers. Respondents were approached to fill in the questionnaires in streets and public places all over the Netherlands The written questionnaire enquired, among other things, whether the consumers owned the previously mentioned technologies. Since the ordinary TV is owned by 98 % of all households in the Netherlands (CBS, 2007), it was not included in the questionnaire. It would have too little discriminating value to be useful. Quota by age groups and sex were used to ensure a representative sample. This resulted in a response of 2094 consumers, varying in age between 16 and 88 years of age (mean = 44.3); 1046 respondents were male, 1048 were female.

Analysis

All questions regarding ownership of the products were recoded to dummies with value 0 = not owning the product, and value 1 = owning the product. The percentages of ownership are displayed in table 3. Clearly, there is a wide spread in diffusion among the technologies.

	Valid N	No	Yes
PDA	2084	88.7%	11.3%
HDTV	2074	88.5%	11.5%
iPod	2079	82.5%	17.5%
FlatPanel TV	2085	80.4%	19.6%
Game Console	2087	77.1%	22.9%
Webcam	2078	68.4%	31.6%
MP3-Player	2080	66.3%	33.8%
Notebook	2084	64.7%	35.3%
Dolby Surround	2078	61.5%	38.5%
Mobile Phone with Camera	2078	51.9%	48.1%
Digital Camera	2084	41.0%	59.0%
Broadband Internet	2073	26.0%	74.0%
Desktop Computer	2083	24.8%	75.2%
DVD-Player	2086	21.5%	78.5%
Mobile Phone	2084	9.3%	90.7%

Table 3: The ownership percentages of the 15 technologies

Since we have no micro-level variables that we want to test, there is no need to build a random-effects model similar to the previous study. Instead, we look for an appropriate binary association measure for a simple 2x2 matrix (figure 2) to indicate combined ownership. The rows represent technology 1 and the columns represent technology 2. A value of 0 means that the technology is not owned and a value 1 means that the technology is owned. The combined ownership is represented by cell d (the individual owns both items).

	0 (C_0)	1 (C_1)
0 (R_0)	a	b
1 (R_1)	c	d

Figure 2: A simple two by two matrix. Cell d represents the ownership links between two technologies.

Sneath and Sokal (1973) mention various binary association measures like the simple matching coefficient, the Yule coefficient and the asymmetric Jaccard coefficient. However, due to the large spread in the frequency distributions none of these measures is applicable. Two widely diffused technologies will automatically have a higher association, because many of the matches in cell d will not be based on chance. If we take, for example, two technologies that are both owned by 90 % of the population, then there is already a guaranteed match in 80 % of the cases. Further, the combined ownership of less widely diffused technologies will be underestimated, because the maximum number of potential matches is lower than with widely diffused technologies. Measures such as the Jaccard coefficient tend to underestimate the low diffused relationships and tend to overestimate the high diffused technologies. Therefore we consider only the number of pairs based on chance. We use the following formula (1) to associate these pairs:

$$(1) \qquad match = \frac{d - \min d}{\max d - \min d}$$

Where:

match	= matching coefficient between 0 and 1
d	= value of cell d
min d	= the minimum value of cell d
max d	= maximum value of cell d

We calculate the association for each possible link between the 15 technologies; this results in 105 different values. These values can once again be written as a vector. We test the interaction of hypothesis 3 with the use of an analysis of covariance (ANCOVA). The dependent variable is the matching coefficient vector for each possible link. The two independent variables are the factor indicating the four types of linking and a variable that represents the perceived links from study 1 (see appendix 2). Furthermore, we consider an interaction term between the two independent variables. If the interaction term between perceived linkages and overlapping functions is significantly lower than the other interaction terms, then hypothesis 3 is considered to be confirmed. As control variables we added the diffusion percentages of both technologies. We indicate the most diffused technology as technology 1, and the other as technology 2.

Results

Appendix 3 displays the results of the binary association procedure. The table forms the basis for identifying clusters in ownership. Each cell represents the matching coefficient between the technologies. The larger the matching coefficient, the larger the probability that two technologies are owned in combination with each other. The first thing we notice on the basis of this table is that there is a relatively strong triangular structure within data among the widely diffused technologies. This can be seen because the matching coefficients are higher for the widely diffused technologies than they are for the less widely diffused technologies.

Despite our correction for guaranteed matches, widely diffused technologies are related to most other technologies. This justifies our choice to use diffusion as a control variable in the models. Table 4 displays the results of the ANCOVA models.

The first model is the base model, which only contains the control variables; these variables already explain 83.9 percent of the variance. The diffusion of a technology is thus by far the most important factor in predicting ownership clusters, even after controlling for guaranteed matches. The second model predicts ownership clusters based only on the factor capturing the types of functional linkages. Compared to the reference category all types of links appear to be equally strong. The third model includes the perceived links and the control variables. There is a significant effect of perceived links on likelihood of ownership, but this is only a modest improvement in R-square compared to the base model. The fourth model includes an interaction term between the type of link and the perceived links. Overlapping functions in interaction with perceived links leads to a significantly lower chance of combined ownership: hypothesis 3 is thus confirmed.

To get more insights into the role of the diffusion of technologies we have also split the dataset into two subsets. One subset contains all relationships of the widely diffused technologies and the other contains the relationships of the less diffused technologies. To determine this we multiplied the diffusion percentage of technology 1 with the diffusion percentage of technology 2 (see table 3). One subset contains the relationships where the multiplication is < 1000 (43 cases) and the other subset contains the other relations (62 cases). For both models we estimated again a base model (models (5) and (6) in the table) and a model with the perceived links variable (models (7) and (8)). Both base models perform well, although the diffusion of technology 2 does not play a significant role in likelihood of combined ownership for the less diffused technologies. In model 7, the perceived links are significant, but not in model 8. The main finding here is that perceived links from study 1 only play a significant role for the less diffused technologies, but not for the more diffused ones.

	Base model (1)	Model categories (2)	Model perceived links (3)	Interaction model (4)	Base Model low diffusion (5)	Base Model high diffusion (6)	Model Perceived links low diffusion (7)	Model Perceived links high diffusion (8)
Intercept	.306	.270	0.281	.245***	.219***	.454***	.188***	.439***
OL		.054**		.109**				
FI		.050***		.045				
SBT		.058***		.079**				
Unk (reference category)		0		0				
Perceived links (from study 1)			.092***	.218***			.166***	.049
Diffusion technology 1 (most diffused technology)	.009***	.009***	.009***	.009***	.010***	.007***	.009***	.007***
Diffusion technology 2 (least diffused technology)	-.005***	-.005***	-.005***	-.005***	-.003	-.006***	-.003	-.006***
Perceived links * OL				-.272**				
Perceived links * FI				-.148				
Perceived links * SBT				-.206*				
Perceived links * Unk				0				
N	105	105	105	105	43	62	43	62
Adj. R^2	0.839	0.855	0.854	0.863	0.825	0.812	0.866	0.817

Table 4: The results of the ANCOVA models predicting the aggregate amount of ownership linkages.
***: $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Study 2 shows first of all that, even after a correction for guaranteed linkages, the rate of diffusion is by far the most important predictor for ownership clusters. There is a relatively strong tendency to buy some technologies first, unrelated to their cluster, and then purchase other technologies, which happen to be part of a technology cluster. Base technologies still remain conditional for adopting peripheral technologies, but they explain relative little variance of the patterns in ownership. Perceived links do have a significant interaction with overlapping functions, as was predicted. However, compared to the base model the improvement in fit is negligible (only 0.024 in adjusted R-squared). Perceived links do play a stronger role in predicting the likelihood of combined ownership in case of lower diffused technologies.

Summarized findings of study 2:

- The diffusion of the technologies is by far the most important factor in predicting ownership clusters.
- Perceived clusters are significantly less predictive for ownership clusters, in case of overlapping functions, compared to other types of links.
- Perceived clusters are significantly predictive for ownership clusters when less diffused technologies are considered, but not in case of highly diffused technologies.

Conclusions and discussion

This paper aimed to contribute to a better understanding of technology clusters in consumer electronics. In this final section we discuss our main findings and their theoretical and practical implications.

As discussed in the introduction, our aim was twofold. First, we aimed at proposing a theoretical mechanism that explains the formation of both perceived clusters and clusters in ownership, while at the same time testing whether perceived clusters are predictors of actual ownership patterns.

We have shown that perceived clusters in consumer electronics are significantly determined by functional linkages based on the underlying infrastructure of such products. This result stems both from a qualitative study uncovering motives behind consumers’ categorizations and from a quantitative analysis of the effects of different types of product properties. Factors not related to functional linkages, such as lifestyle considerations, are not good predictors of perceived clusters in consumer electronics.

While perceived clusters are primarily based on functionality, ownership clusters are more likely to be based on the diffusion of the technologies. Ownership clustering starts from a broad base of technologies that most people own, after which consumers adopt additional parts of one or more clusters according to individual preferences and external circumstances. Starting to adopt a cluster itself may be based on lifestyle, but how the cluster is composed is based on the types of linkages.

The main implication of these results for the literature on technology clusters is that a clear conceptual distinction between perceived and ownership clusters is worthwhile to pursue if one wants to understand the composition of clusters and not take them as exogenous entities. A practical implication of our results is that it makes sense for consumer electronic stores (as it is often the case) to arrange their products in a manner that reflects the perceived clusters. Consumers do use taxonomic concepts as the strongest guide to relate consumer electronics with each other. Consumers should then be stimulated to perceive links between a new product and their owned set of technologies based on a shared infrastructure. The finding that perceived clustering does influence ownership clusters only for low diffused technologies may also have managerial implications. In terms of advertising this would mean that the introduction of a new technology can be done by pointing at a relationship with functionally related technologies. For example, a PDA can best be displayed with technologies it can connect to like a notebook, or with other gadget technologies that have overlapping functions.

Our second aim in this paper was to investigate the role of prior knowledge on technology clusters. We have found that consumers with a large knowledge base perceive clusters based on functional linkages, but without a strong preference for one of the types of linkages considered. Our theoretical prediction was that more expert consumers would use functional interdependences more than overlapping functions. We did not find evidence for this specific claim but we discussed possible explanations. However, we did find a direct positive relationship between knowledge base and the probability of linking. This implies that high knowledgeable individuals are able to place the innovations into a more detailed context. It exemplifies the fact that in any innovation communication process it is important to tailor the message to the consumer knowledge base. Based on our results, this is more important than differentiating between types of linkages.

Finally, we wish to conclude by indicating two avenues for further research. On one hand, a further challenge relates to situations in which functional linkages also depend on product attributes. This is likely to be the case when infrastructural linkages differ across brands. Take the example of the choice of a game console cluster. This cluster starts with the purchase of a television, after which almost any type of game consul can be bought. Once the choice for a certain brand or type of game console has been made (e.g. Nintendo Wii, Xbox or Playstation 3), consumers are locked in a certain path. They are bound to the products (video games, controllers and other extensions) that the specific consul has to offer, unless they are willing to invest in another type of console. The knowledge base of consumers also gets more specialized as the cluster gets more specialized. In case of switching, consumers can apply many of their basic skills in the new cluster, but the more specialized knowledge cannot be applied in the new situation.

Further research could also focus on other product domains, to find out how consumers relate products that are not explicitly physically connected to each other. This gives a larger probability of linking technologies based on aspects of the taxonomy of Yeh and Barsalou (2006) other than taxonomic concepts. Also the addition of some less known or even non-existent technologies to a set of technologies could provide interesting results in a future study. Relatedly, research could aim at a richer conceptualization of technology clusters by taking into account more attribute levels. Diversified product attributes may render a certain product more attractive than another even when the two are functional substitutes.

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Appendix 1: The typology of all possible links: OF = Overlapping functions, FI = Functional Interdependencies, SBT = Shared base technologies, Unk = Unknown, no relationship

	Pda	HDTV	Ipod	FPTV	Game	Webcam	Mp3	NB	Dolby	MPC	Dicam	Broadint	Desk	DvD	MP
Pda															
HDTV	Unk														
Ipod	SBT	Unk													
FPTV	Unk	OF	Unk												
Game	Unk	FI	Unk	FI											
Webcam	SBT	Unk	SBT	Unk	Unk										
Mp3	OF	Unk	OF	Unk	Unk	SBT									
NB	FI	Unk	FI	Unk	OF	FI	FI								
Dolby	Unk	FI	SBT	FI	FI	SBT	SBT	FI							
MPC	OF	Unk	OF	Unk	Unk	Unk	OF	FI	Unk						
Digicam	SBT	FI	SBT	SBT	SBT	SBT	SBT	FI	SBT	OF					
Broadint	SBT	Unk	SBT	Unk	FI	SBT	SBT	FI	SBT	Unk	SBT				
Desk	FI	Unk	FI	Unk	OF	FI	FI	OF	FI	Unk	FI	FI			
Dvd	Unk	FI	Unk	FI	SBT	Unk	Unk	Unk	FI	Unk	Unk	Unk	Unk		
MP	OF	Unk	OF	Unk	Unk	Unk	OF	Unk	Unk	OF	Unk	Unk	Unk	Unk	
TV	Unk	OF	Unk	OF	FI	Unk	Unk	Unk	FI	Unk	FI	Unk	Unk	FI	Unk

Appendix 2: The results of binomial logistic random effects model. The numbers represent the number of times that the connection was made. The asterisks represent the p-value of the binomial random effects model: ***: $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The smaller the p-value, the larger the likelihood that the perceived links are not based on chance.

	Pda	HDTV	Ipod	FPTV	Game	Webcam	Mp3	NB	Dolby	MPC	Dicam	Broadint	Desk	DvD	MP
Pda															
HDTV	2														
Ipod	16**	4													
FPTV	1	40***	1												
Game	15**	9*	9	12**											
Webcam	22***	6	8	5	29***										
Mp3	12**	1	42***	1	7	6									
NB	27***	2	10*	3	27***	39***	9								
Dolby	4	21***	15**	25***	10*	10*	19***	8							
MPC	25***	2	12*	2	3	6	11*	8	2						
Digicam	19***	4	15**	6	6	9	13*	9	5	30***					
Broadint	20***	5	8	6	31***	43***	6	37***	12*	5	8				
Desk	20***	4	7	7	32***	42***	6	40***	13**	3	7	42***			
Dvd	0	35***	6	39***	11*	5	7	0	29***	3	4	4	3		
MP	25***	2	13*	1	1	4	12*	6	5	45***	22***	3	3	2	
TV	1	37***	2	44***	10*	6	1	2	23***	1	4	5	5	40***	2

Appendix 3: The results of the binary association procedure.

	Pda	HDTV	Ipod	FPTV	Game	Webcam	Mp3	NB	Dolby	MPC	Digicam	Broadint	Desk	DvD
Pda														
HDTV	0.22													
Ipod	0.30	0.27												
FPTV	0.34	0.62	0.29											
Game	0.38	0.32	0.39	0.30										
Webcam	0.53	0.46	0.53	0.42	0.57									
Mp3	0.50	0.43	0.42	0.40	0.51	0.51								
NB	0.71	0.50	0.52	0.46	0.48	0.47	0.46							
Dolby	0.63	0.69	0.50	0.62	0.52	0.50	0.47	0.45						
MPC	0.69	0.60	0.80	0.57	0.73	0.69	0.68	0.63	0.60					
Digicam	0.80	0.74	0.64	0.79	0.66	0.71	0.70	0.72	0.72	0.60				
Broadint	0.90	0.86	0.89	0.84	0.89	0.90	0.86	0.81	0.79	0.77	0.65			
Desk	0.88	0.85	0.78	0.85	0.84	0.83	0.78	0.58	0.76	0.61	0.65	0.56		
Dvd	0.90	0.89	0.84	0.92	0.87	0.78	0.78	0.75	0.87	0.68	0.68	0.51	0.47	
MP	0.99	0.94	0.98	0.90	0.96	0.95	0.92	0.93	0.86	0.97	0.80	0.71	0.62	0.51