A knowledge based model for learning about innovation

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Abstract

Innovation is a process that involves searching for new information. This paper builds upon theoretical insights on individual and organizational learning and proposes a knowledge based model of how actors search for information when confronted with innovation. The model takes explicitly into account different search channels, both local and non local, and relates their use to the knowledge base of actors. We also provide an empirical validation of our model based on a study on the search channels used by a sample of Dutch consumers when buying new consumer electronic products. Finally, we discuss the general implications of our findings.

Introduction

Innovation is a process that involves searching for new information. According to (March, 1991), firms have to balance their search effort for new knowledge (exploration), with the exploitation of existing knowledge. This search for new information prior to innovating is not only limited to the behaviour of organizations, but also characterizes other types of actors confronted with innovation, for example consumers.

The *first* aim of this paper is to contribute to a theory that explains the relation between an actor's knowledge base, the use of different channels for information search and the intention to buy or adopt an innovation. This will be done by combining consumer behaviour arguments (e.g theory of innovation adoption, Rogers, 2003; theory of planned behaviour Ajzen, 2005; consumer learning models, Johnson and Russo, 1984, Beatty and Smith , 1985; Srinivasan and Ratchford, 1991; Gregan-Paxton, 1997; cognition, Yeh and Basralou, 2006) with concepts used to explain innovative behaviour (e.g. evolutionary economics, Nelson and Winter 1982, Aversi et al, 1999, Devetag, 1999); knowledge based view, Cohen and Levinthal (1990).
This theoretical exercise leads us to integrate theories that are formulated on the individual level with theories (evolutionary economics, knowledge based view) developed for organizational behaviour. Combining theories on multiple levels provides us with the opportunity of developing a quite general model. At the same time this exercise requires some caution, because although the effects found may be there, the driving mechanisms behind the effects could be completely different. Among all theories from which we draw inspiration, the knowledge based view may be easily applied both at the individual and organizational level. In fact, Cohen and Levinthal (1990), build their understanding of organizational learning processes starting from insights found at the individual level. They carefully stress the

conceptual issues involved in moving from an individual to an organizational level, but they ultimately demonstrate the validity of their knowledge based framework at both levels.
In order to build our model, we rely upon three important behavioural assumptions.
The first underlying behavioural assumption that we will make is that actors are characterized by bounded rationality (Simon, 1978) so that actors are constrained in terms of the cognitive and computational resources that they can exploit to absorb information, solve problems and take decisions. This behavioural assumption bears indeed validity both at the individual and at the organizational level. It also justifies our focus on the role of an actor's knowledge base.
Second, following the evolutionary economics view, actors use search to gather information aimed at either innovation or imitation (Nelson and Winter, 1982). Search is assumed to work as a mechanism spurring change and learning which is characterized both by a high level of uncertainty and by a contingent nature.
Third, actors are embedded in social networks and their behaviour relies on a combination of social and individual learning, rather than being the result of an isolated rational decision making process (see for instance Aversi et al 1999 at the level of consumer and Greve (1998) and Levitt and March, 1988, at the level of organizations).

The *second* aim of this work is to provide an empirical validation of our theoretical model based on a study where we analyse the empirical relationships between the ownership of consumer electronic products among Dutch consumers and their use of different communication channels. A recent contribution that very much relates to our own study comes from Borgatti and Cross (2003). They propose that information seeking is a function of "*(1) the extent to which a person knows and values the expertise of another, (2) the accessibility of this person and (3) the potential costs incurred in seeking information from this person."* Their empirical findings indicate that search costs are not significant for the choice of the source of information. However, in developing our theory we will use search costs as the prime unobserved explanatory mechanism for information search channels. Borgatti and Cross (2003) do provide several possible reasons why search costs were not significant, which ultimately justify the use of search cost as an explanatory factor.
Our empirical results can help advertisers and marketers of innovative consumer electronics to further develop effective communication strategies through the various channels in relation to the consumers existing knowledge base. Second, not only managers may use our results to improve their marketing strategy, but more generally they will gain more insights on the search behaviour of consumers or other actors.
Although we use consumers and consumer electronics as a test case, our aim is to develop a theory that is more broadly applicable; this is also our motivation for integrating organizational theories with individual level theories. This approach can result in a theory that is applicable on different types of actors.
In the next section we will develop a theoretical framework for the relationship between the knowledge base and the channels of information search. After this we will continue by presenting our research methods, results and discussion.

Theory

Knowledge base and learning

Following Rogers (2003) a technological innovation can be defined as a technology that is perceived to be new by an actor. This innovation can be viewed as being stand-alone or as being part of a perceived larger whole, for example a technology cluster (LaRose and Hoag, 1996, Rogers, 2003; Vishwanath and Chen, 2006) or a product domain (Goldsmith et al, 1995; Van Rijnsoever en Donders). The ownership of parts of this larger whole can be viewed as an indicator for the knowledge that an actor has of the total larger whole. In this paper we will focus on the level of the product domain, although our theory may also be applicable on

other levels of perception. Our dependent variable is then the intention to buy/adopt new products.

We will start building our theory from the knowledge based arguments used by Cohen and Levinthal (1990). They claim that agents absorb new knowledge using their existing knowledge base; the knowledge and experiences they already have gathered in the past. A limited knowledge base implies bounded rational decision making. Agents do not have the information, or the mental capacities to make fully rational choices (Simon, 1955; March, 1978; Nelson and Winter, 1982). This certainly applies to decisions that are loaded with high amounts of uncertainties like the decision to innovate or not.

To enhance the existing knowledge base new information has to be searched and learning has to take place. Evolutionary economics has also used similar arguments to explain behavioural search patterns. Following Cyert and March (1963), Nelson and Winter (1982) assume both a "local" search, to incrementally improve existing techniques, and an imitation mechanism, by which an organization can adopt behavioural patterns from competitors (Lewin et al, 2004). These theoretical ideas can easily be applied to the individual level, as has been done previously by (Bettman et al, 1998; Aversi et al, 1999; Devetag, 1999).

According to Bandura (1977), humans learn either individually (through trial and error) or socially (by observing the behaviour of others). In general the latter is more efficient than the former, because one can choose only to adopt successful behaviour (Boyd and Richerson, 1985; Richerson and Boyd, 2005). Once the new behaviour has been adopted and proven successful, the behaviour is more likely to be repeated (Homans, 1974; Bandura, 1977; Gavetti and Levinthal, 2000;. A process of incremental improvement takes place, which can allow the behaviour to be developed further into a skill or routine. In consumer research, it has indeed been shown that prior knowledge leads to more routinization in learning about new products, Wood and Lynch Jr. (2002).

Depending on the newness of this idea, adopting a first technology in domain is a step that involves a relative large amount of risk (Hoeffler, 2003; Rogers, 2003). The knowledge base is formed after the adoption of this first part. Following Bandura (1977) and the performance feedback theories by Greve (1998), for the next decision to adopt the actor can:

- Use individual learning and asses the potential in view of own previous experiences (Gregan-Paxton and Roedder John, 1997; Yeh and Barsalou, 2006). This is called internal search in consumer behaviour theory (Blackwell et al, 2001)
- Use social learning and asses the potential in view of current experiences of others (if available) (Blackwell, 2001; Rogers, 2003; Richerson and Boyd, 2005). This is called external search in consumer behaviour theory (Blackwell et al, 2001)

If the actor assesses potentially positive results from adopting the next technology within the domain, adoption becomes more likely. Since the following parts all fall within an existing knowledge base, they entail less uncertainty and they are more easily adopted. In this way they represent incremental innovation within an existing technological trajectory (Dosi 1982, Gatignon et al. 2002).

A knowledge base is therefore a means to enable more rational decision making. In the next section we will relate the size of the knowledge base to various forms of learning and the intention to adopt new innovations; for each relationship a hypothesis will be formulated. Our research model is depicted in Figure 1.

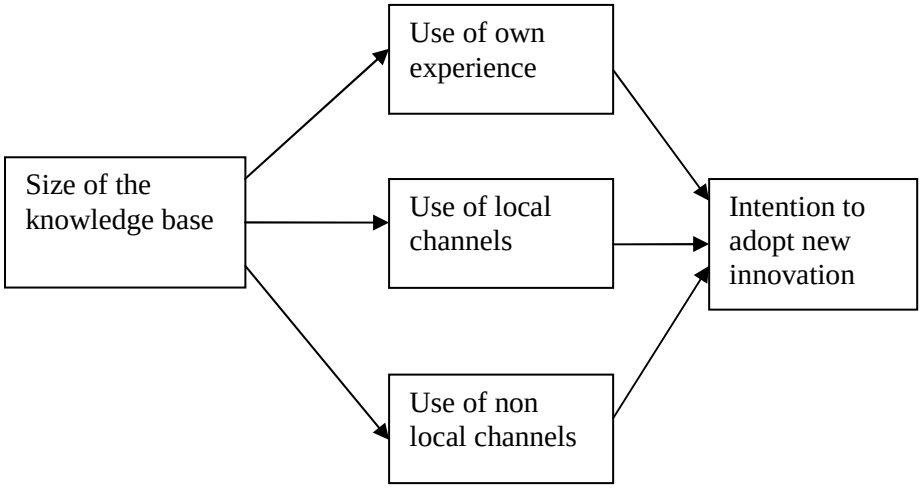

Figure 1: The proposed relationship between the knowledge base, the channels of information search and the intention to adopt new innovations.

Knowledge base and channels for information search

The size of the knowledge base can influence the type of learning used in the search for new technologies. As told previously, actors can learn through their own experience or through communication channels. In this paper we discern two types of search channels, local[1] and non-local. Local search channels are the relations an actor has with the people with whom he has direct interaction in his social environment (e.g. friends and family); non-local search channels are the information sources that do not require a direct local-interaction from the actor (e.g. watching TV, listening to the radio, surfing the internet). This distinction runs in our case parallel to the distinction between personal influence and mass media (Katz and Lazarsfeld, 1964), but their distinction is not applicable to other types of actors, so we will use the broader definition. The choice of an information source to evaluate a product depends on the minimization of the amount of effort (or search costs) one has to make to gather the required information (Moorthy et al, 1997). There are many factors that determine the search costs. According to Borgatti and Cross (2003) these search costs can consist of loss of reputation by admitting ignorance, obligations resulting from knowledge exchange and physical distance. Examples of other types of costs can be other forms of distance (cognitive, geographical, organizational, social or institutional; see Boschma, 2005) the amount of time invested, the actual monetary costs; this depends on the actual context of the actor. We assume that the amount of effort is lowest if one uses only the own experience, then a local search requires least effort; the non-local search requires most effort.
Actors with a smaller knowledge base are not able to asses all new innovations with the use of their own experience (Rogers, 2003). They can however get ideas or asses the potential of a product by observing their peers or communicating with them (Richerson and Boyd, 2005). This means that they can learn socially from individuals that already posses the technology. Since the local search channels provide al the information that is required, there is little need to put any effort in non-local channels.
Actors that posses a more than average amount of technologies also have a knowledge base that is larger than average. After a certain critical point, extending that knowledge base through local search channels becomes ineffective. The use of these channels will therefore decline. Because these actors have already exploited most information available from local

[1] The term local search does not apply here as used by Nelson and Winter (1982) and Rosenkopf and Almeida (2003). They state that a local search is a search that is close to actors existing competences. In our view all searches are also directly related to the knowledge base, but that does not imply anything about the information search channels used. Our term local search is defined in terms of direct contact.

channels, they have to rely more on information gathered from non-local channels, and also again from their own previous experiences.
These relationships resemble theoretical models used by Johnson and Russo (1984) and (Moorthy et al, 1997), who also claim that the knowledge base is related in an inverted U-shape to external search. External search is there defined as: "*The degree of attention, perception and effort directed toward obtaining environmental data or information related to the specific purchase under consideration*" (Beatty and Smith, 1985). The difference here is that we relate the inverted U-shapes specifically to social learning processes and various search channels, while the linear relationship is related to individual learning. Thereby our model can be viewed as an extension of the model by Johnson and Russo (1984), for which we do distinguish between different search channels. Furthermore, our arguments are based on economic arguments related to the search effort, rather than on cognitive abilities. Moorthy et al (1997), also use economic arguments to explain the inverted U-shape, however their arguments do not involve a comparison between the knowledge bases of various actors, an element that is crucial to for any explanation that involves social learning. Another interesting contribution comes from Kerstetter and Cho (2004) who very specifically relate past experience to the use of various search channels in the domain of tourism search behaviour. However, they do not include the inverted U-shape in their statistical results.
Our theoretical arguments on the relationship between knowledge base and the use of information search channels can be summarized in the following three hypotheses:

H1: The larger the knowledge base of an actor, the more likely he is to learn about new products using his own experience.
H2: The relationship between size of the knowledge base of an actor and the likelihood of using information from local search has the form of an inverted U-shape.
H3: The relationship between size of the knowledge base of an actor and the likelihood of using information from non local search has the form of an inverted U-shape.

Knowledge base, search channels and the intention to adopt new innovations

Does the size of the knowledge base influence a consumer's aspiration to purchase even more new products? In answering this question we will limit ourselves to the knowledge based arguments. From what we stated above, it follows that the answer is affirmative, a broader knowledge base reduces uncertainty about a product, which increases the likelihood of adoption.
To answer the question in more detail we will turn to the theory of planned behaviour by Ajzen, (2005). This theory states that behavioural intentions are influenced by the attitude towards the behaviour, a subjective norm (the perception of how the behaviour is valued by others), and the perceived behavioural control. In our application of the theory the knowledge base influences attitude towards the behaviour and the perceived behavioural control.
The argument for the attitude towards the behaviour goes as follows: as you own certain products that are conditional for being able to use other products, you are also better able to asses how these peripheral products might be advantageous for you. If you own for example a computer with a broadband internet connection, then you are better able to asses the potential value of a webcam, compared to a situation in which you do not own these base technologies (Gregor Paxton and Roeder John, 1997; Yeh and Basralou, 2006). If these previous experiences with these technologies are positive, it is expected that the consumer will develop a positive attitude towards the new technology. This positive attitude will increase the intention to adopt the new innovation (Ajzen, 2005).
A greater knowledge base will also increase the perceived behavioural control. Adopting an innovation is per definition a bounded rational decision process, because innovation is always connected to uncertainty (Greve, 1998, Rogers, 2003; Becker, 2004). Having more knowledge

and experience however can reduce this uncertainty dramatically, which in turn will increase the perceived behavioural control and therefore the intention to adopt a new product.
There is however a limit to the amount of different products one can own in the same production domain, and therefore there is also a limit to the amount of products one can aspire to own. For each product an individual owns there is a product less he can aspire to own. Since the knowledge base is related to the actual ownership of innovations, we expect and an inverted U-shaped relationship:

H4: The relationship between the size of the consumer knowledge base and the intention to adopt new innovations has the form of an inverted U-shape.

The subjective norm is influenced by local and non-local communication channels. If the information from these channels is favourable, the subjective norm will change positively and the intention to purchase a new product will increase. At the same time, the larger the knowledge base, the better the actor is able to make his own judgements, and the less likely it is that the subjective norm will be of influence.

H5. The use of own experience is to asses new technologies is positively related to the intention to adopt new innovations.
H6. The use of local communication channels to assess new technologies is positively related to the intention to adopt new innovations.
H7. The use of non-local communication channels to assess new technologies is positively related to the intention to adopt new innovations.

From these hypotheses it follows that:

H8. The relationship between the size of the consumer knowledge base and the intention to adopt new innovations is mediated by the consumer's experience, local channels and non-local communication channels.

In the next section we proceed to empirically validate our model and test the formulated hypotheses for the decision to purchase consumer electronic products in a sample of Dutch consumers.

Empirical analysis

Data and methods

A survey was administered among Dutch consumers by students of a research methodology course. 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 (mean = 44.3); 1046 respondents were male, 1048 were female.
The written questionnaire enquired, among other things, whether the consumers owned one of 15 technologies or wanted to own it. The technologies were:

1. PDA
2. HDTV
3. iPod
4. Flatpanel television
5. Game consul
6. Webcam
7. MP3-player
8. Notebook or laptop
9. Dolby-surround system
10. Mobile telephone with camera function

11. Digital camera
12. Broadband internet
13. Desktop
14. DVD-player
15. Mobile Phone

We realize that some of these products have overlapping functionalities. A game consul for example might also function as a DVD player. These overlapping functionalities were controlled as much as possible during the data collection by asking very specific questions that excluded these possibilities.

All questions were asked in the form:

I own a (*one of the 15 products*) O – No, and I do not intend to purchase this product
O – No, but I do intend to purchase this product for sure
O – Yes, this is the first time own this product
O – Yes, this is a replacement purchase

All questions regarding ownership of the products were recoded to dummy variables with value 0 for the answers of not owning the product, and value 1 for the answers indicating ownership of the product. The same procedure was followed for intention, all answers indicating that the respondent intends to buy the product were coded to value 1, and all other answers got the value 0.

Further, the questionnaire enquired about the use of various search channels and the amount of influence these channels had according to the respondent when purchasing new consumer electronics.

In the previous discussion we have treated the knowledge base as a homogenous concept. However there is a theoretical discussion whether knowledge base is a homogeneous concept, or whether it has multiple dimensions (Alba and Huchinson, 1987; Kerstetter and Cho (2004). Because of this discussion, the knowledge base was measured in two different manners: (1) by the number of consumer electronics products the respondent owned, (2) by a set of five point Likert scale questions measuring the knowledge base. The exact operationalization is presented in Table 1.

Variable	**Measurement**
Knowledge base	(1) The amount of consumer electronic products owns (2) The following questions (using a 5 point Likert scale) 1. I always try to participate in the latest trends in consumer electronics. 2. I am fashionable in the area of consumer electronics. 3. I try to remain aware of the latest trends in consumer electronics. 4. I am always fast in purchasing new consumer electronics. 5. I think it is important to own new consumer electronic products.
Use of search channels	I get the idea to purchase new consumer electronics by: (using a 5 point Likert scale) 1. My own experience 2. Family living in my household 3. Friends and relatives 4. Other people around me (school or work for example) 5. People on the street 6. Through shops where I can purchase the product 7. Radio and Television 8. Advertisements and folders 9. Internet sites (no e-mail and chatting)
Intention to buy new products	The amount of products a consumer intends to buy.

Table 1: The measurement of the variables.

We dealt with missing values by using multiple imputation with the PRELIS program (Jöreskog and Sörbom (2006), this resulted in 2090 usable cases (4 cases could not be imputated).
We performed a principal components analysis with a varimax rotation on the items measuring the influence of various search channels. Three factors were extracted that roughly corresponded with the three types of search channels we identified earlier (see Table 2). Component 1 corresponds to non-local search channels, component 2 to local search channels, and component 3 to own experience. These results were the basis for our model of search channels in the statistical models. For theoretical reasons we used the influence of internet sites in non-local search channels, rather than own experience, despite its higher factor loading. The factor loading can be explained by the fact that the search costs of the internet are lower than conventional channels (Bakos, 1997; Dellarocas, 2003). This made the own experience a single indicator variable, for which we assumed no measurement error.

	Component		
	1	2	3
My own experience			.809
Family living in my household		.686	
Friends and relatives		.821	
Other people around me (school or work for example)		.535	
People on the street	.498		
Through shops where I can purchase the product	.698		
Radio and Television	.795		
Advertisements and folders	.763		
Internet sites (no e-mail and chatting)	.422		.641

Table 2: The results of the Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Values < 0.4 were suppressed for reasons of clear presentation.

The descriptive statistics and the correlations of the ownership indicators are given in Table 3.

	Mean	Std. Deviation	Knowledge Base	Knowledge Base^2	Own experience	Local Search Channels	Non-local Search Channels
Knowledge Base	6.495	2.994					
Knowledge Base^2	51.142	39.322	.956**				
Own experience	3.284	1.078	.281**	.263**			
Local Search Channels	9.422	2.331	.220**	.172**	.218**		
Non-local Search Channels	13.582	3.753	.367**	.340**	.233**	.291**	
Intention to adopt	1.433	1.551	.076**	.016	.092**	.086**	.151**
Valid N (listwise)	2090						

Table 3: The descriptive statistics and the correlation matrix. *: $p < 0.05$; **: $p < 0.01$.

The two different measures of knowledge base also require the use of different statistical procedures. The type of linkages included in our model is best estimated using a structural equation model. However, because the ownership of certain products is dependent on the ownership of other products (Rijnsoever and Castaldi, 2007), the correlation between the two indicators varies, this causes problems to calculate an interaction term. Further the large error-covariance between the dummies predicting the intention to adopt a certain innovation and the ownership of those innovations makes it more problematic to calculate an interaction term in a structural equation model setting that describes the quadratic effect of knowledge base.
For the ownership indicator we therefore resort to other regression techniques. The dummy variables for each of the two concepts were summed together to form their respective variables.

To test hypothesis 1 we performed an ordinal regression (McCullagh, 1980; McCullagh and Nelder, 1998), since the dependent variable is a five point Likert scale. The hypotheses 2 and 3 are tested using an OLS regression, because the variables are approximately continuously normally distributed. In order to test the inverted U-shapes we also included a square term for the size of the knowledge base. To test hypotheses 4 to 7 we fit a quasipoisson[2] model (McCullagh and Nelder, 1998; Agresti, 2002), because of the categorical nature of the dependent variable. Hypothesis 8 regarding the mediating effects was tested by testing a quasipoisson model with as independent variables the knowledge base variables, the opinion leadership variables and the communication channel variables. Following Baron and Kenny (1986); Bennet (2000); MacKinnon et al (2007) a mediating effect is established if:

- The model regressing only the knowledge base variables on the intention variables gives significant predictors for these variables
- The model regressing only the knowledge base variables on the communication variables gives significant predictors for these variables.
- The model regressing communication channel variables on the intention to buy new products gives significant predictors for these variables.
- In a model regressing the knowledge base variables and the communication channel variables on the intention to buy new products, the predictors for the knowledge base variables have become significantly smaller.

Normally these mediating effects are evaluated with the use of a Sobel test (Sobel, 1982; Baron and Kenny, 1986; Soper, 2007), however since our dependent variable is categorical, rather than continuous, this method is less reliable (Preacher and Hayes, 2004; MacKinnon et al, 2007). Instead we rely on a method based on bootstrapping[3] (MacKinnon et al, 2007), using a macro in SPSS with 5000 bootstrap samples that is described in Preacher and Hayes (2004). The bootstrap results indicate the effect of an independent variable through the mediator and its confidence interval. If the 95 % confidence interval includes zero, then the independent variable is not mediated.

For the second type of indicator of the knowledge base we fitted a structural equation model using the LISREL 8.80 program (Jöreskog and Sörbom (2006)). From the Likert-scale questions measuring knowledge base the LISREL program extracted a latent variable that represents the knowledge base. The squared variable of the knowledge base (which is an interaction of the variable with itself) was obtained by following a two-step tecnique (Ping, 1996) implemented in an EXCEL template (Ping, 2003). By averaging the measurement loadings of the indicators and the error terms, the EXCEL template calculated a factor loading

[2] A Poisson distribution assumes that the mean of a random distributed variable is equal to its variance. For a quasipoisson distribution this needs not be the case. The estimated were done with the R-program (R-development core team, 2007).

[3] Bootstrapping is a nonparametric approach to effect-size estimation and hypothesis testing that makes no assumptions about the shape of the distribution of the statistic (Preacher and Hayes, 2004).

and measurement error for a single indicator variable that is the squared term of the original latent linear predictor. For the use of search channels we use the same indicators as in the previous model. A latent variable was extracted from the dummy variables that represent intention to adopt new innovation. We allowed for error-covariances among the dummy variables if the modification indicated that those were necessary. In estimating the structural equation model using maximum likelihood estimation, the covariance matrix turned out to be not positive definite; therefore we used Unweighted Least Squares Estimation, which is the preferred alternative (Saris and Stronkhorst, 1984). The model we tested is given in figure 2

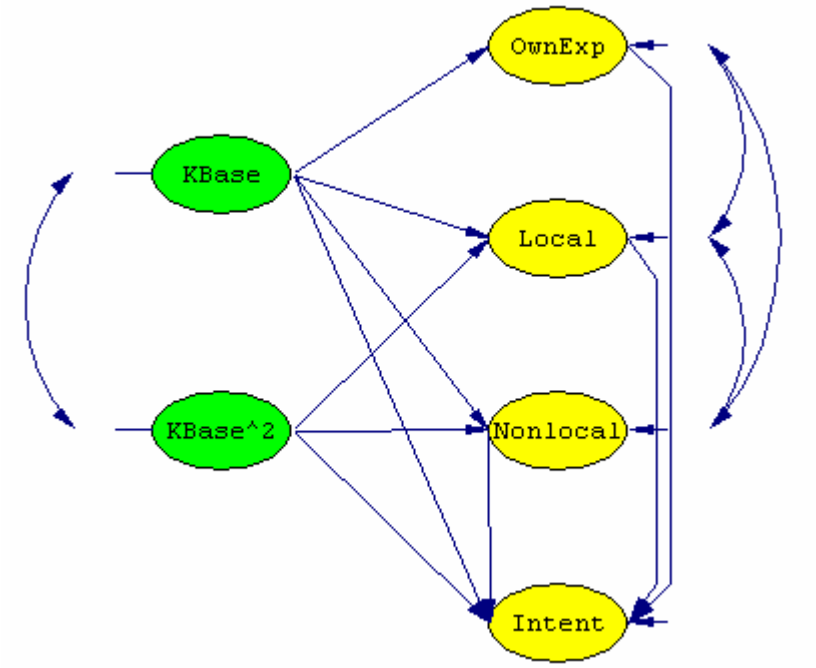

Figure 2: The structural model estimated in LISREL: KBase = Knowledge Base, KBase^2 = Knowledge Base Squared, Ownexp = Own Experience, Local = Use of Local Channels, Nonlocal = Use of Non-local Channels, Intent = Intention to adopt new innovations. The one headed arrows represent the relations that are tested, the two headed arrows represent error-covariances. For reasons of space the measurement model is not shown here.

Results

We start by discussing results of the analyses predicting the use of communication channels when knowledge base is measure with the first indicator, based on product ownership (see. Table 4). The first column shows estimates from an ordinal regression model of the influence of knowledge base on the use of own experience. The knowledge base has a positive influence on the evaluation of the products through own experience; this confirms hypotheses 1. The use of local search channels is related to the knowledge base in the form of an inverted U-shape with turning point at respectively 9.55 products (hypothesis 2). Non-local search channels are only positively related to the existing knowledge base, and the squared variable is only significant at 10%. Thus hp 3 is partly rejected.

	Own Experience	Local Search Channels	Non-Local Search Channels
(Constant)		7.497**	10.249**
Knowledge Base	.205**	.507**	.603**
Knowledge Base^2	-.002	-.027**	-.011
(Nagelkerke) R^2	0.086	0.065	0.135

Table 4: The results of the analyses predicting search channels. The first column predicts the use of own experience to evaluate new consumer electronics, using ordinal regression. The other two columns predict the use of communication channels by means of OLS regression. *: $p < 0.05$; ** $p < 0.01$.

Table 5 presents the results of three quasi-Poisson regression models predicting the intention to buy new products. The first model contains the knowledge base variables as predictors, the second the search channels and the third model combines the former two. As performance indicators for the model we have given the deviance (Agresti, 2002). All models represent a significant improvement compared to the empty null model.
For model 1, we find a significant U-shaped relationship (turning point at 7 products) between the size of the knowledge base and the number of products intended to buy; hypothesis 4 is thus confirmed. In model 2, the intention to buy new products is positively related to the own experience and the use of non-local search channels. This confirms hypotheses 5 and 7, but rejects hypothesis 6. The combination made in model 3 has as a consequence that the own experience loses much of its predictive value.

	Intention to buy
Deviance Null model	3699.9
(Constant)	0.626**
Knowledge Base	0.330**
Knowledge Base^2	-0.023**
Deviance model 1	3521.1**
Constant	-0.542**
Own experience	0.059*
Local Search Channels	0.019
Non-Local Search Channels	0.038**
Deviance model 2	3601.0**
(Constant)	-1.209**
Knowledge Base	0.299**
Knowledge Base^2	-0.023**
Own experience	0.059*
Local Search Channels	0.006
Non-Local Search Channels	0.036**
Deviance model 3	3454.9**

Table 5: The results of the quasi-Poisson regression model predicting the intention to buy. The first model contains the knowledge base variables as predictors, the second the communication channels and the third model combines model 1 and 2. As performance indicator the deviance is given. *: $p < 0.05$; **: $p < 0.01$.

The results of the bootstrap estimation to estimate the mediating effects are displayed in Table 6. We find that all communication channel variables have a mediating effect on the relationship between knowledge base and the intention to buy. However this is also partly due to the large sample size, which makes even the smaller effects visible. We see that the mediating effect by non-local search channels is the largest, while the mediating effects by local search channels are relatively small. This is due to the fact that since there is no significant relationship between the mediator and the dependent variable, there can also be no mediating effect (Baron and Kenny, 1986).

Independent variable	**Mediator**	**Bootstrap Effect**
Knowledge Base	Own Experience	0.0109**
Knowledge base	Local Search Channels	0.0086**
Knowledge base	Non Local Search Channels	0.0300**

Table 6: The results of the test for mediating effects using bootstrap estimation. *: $p < 0.05$; **: $p < 0.01$.

Table 7 present the results of the structural equation model that uses the Likert scale questions as indicators for the knowledge base. The dependent variables are displayed horizontally, the independents vertically. The cells represent the standardized estimates of each path and their p-value. For each dependent variable we also report the R-square value as measure for explained variance. The model, despite being a large one, has an excellent Goodness of Fit Index of the model is 0.97. The Root Mean Square Error of Approximation (RMSEA) is 0.067 which can be considered as a good fit. For this model the measurement matrices can be found in the appendix.

	Own experience	Local Search Channels	Non-local Search Channels	Intention to adopt new innovations
Knowledge Base	0.38***	0.13***	0.80***	0.39***
Knowledge Base^2		-0.15***	-0.16***	-0.24***
Own experience				-0.05***
Local Search Channels				-0.01
Non-local Search Channels				0.21***
R^2	0.14	0.03	0.60	0.30

Table 8: The results of the model using the Likert scale questions as measure for knowledge base. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$. The GFI is 0.97, the RMSEA is 0.067

The model convincingly shows that there is a significant relationship between the size of the knowledge base and the use of information channels. It predicts a linear relationship between the knowledge base and the use of own experience, confirming hypothesis 1; further it predicts an inverted U-shape between knowledge base and local-channels (the R-squared is relatively low though), which is in line with hypothesis 2. Also the U-shape as predicted in hypothesis 3 is present. The turning point for non-local channels is further to the right than for local channels, which indicates higher search costs. The model also confirms the inverted U-shape between the intention to adopt new innovations and knowledge base

The model rejects hypotheses 5 and 6, there is a very small but significant negative relationship the use of own experience and the intention to adopt new innovations. There is no relationship between the use of local channels and the intention to adopt new innovations.

Hypothesis 7, the relationship between the intention to adopt and the use of non-local channels is confirmed again however. The indirect effects of knowledge base through the search channels are also significant (knowledge base on intention: 0.15, $p<0.001$; knowledge base squared: -0.03, $p<0.001$), which proves the mediating effects of hypotheses 8.

If we compare the models that resulted from the different indicators for knowledge base, we see that there are many similarities between them; this enhances the validity of our results.
With both measurement methods, hypotheses 1, 2, 4, 7 and 8 were confirmed; we therefore consider these as accepted. In the structural equation model hypothesis 3 was convincingly confirmed, contrary to the OLS model. This is most likely due to the fact that the amount of technologies an individual owns (on a scale varying from 0-15) is a not refined enough scale to show the predicted effect at the 5 % significance level; there is an effect at the 10 % level though. Since the effect does significantly appear in the structural equation model (with an explained variance of 60 %), we also consider hypothesis 3 as accepted. Hypothesis 5 was rejected in the quasi-Poisson model, while the structural equation model revealed a small but significant negative relationship. In the structural equation model however, we assumed no measurement error for this single indicator variable, an assumption that is probably not entirely true; we are therefore cautious in interpreting these results. Given the relative small effect and this assumption, it is probably safe to neglect the negative relationship produced by the structural equation model. We still consider hypothesis 5 rejected however. Both models do agree on the rejection of hypothesis 6, which is discarded without further discussion.

Discussion

The theoretical model proposed in this paper offers a knowledge-based perspective on the different search channels that actors use to inform their adoption decision. The basic argument that we used is that actors will attempt to minimize their search efforts; they will therefore prefer to first use their own experience (their knowledge base) to evaluate or search a new concept. If the own experience is insufficient, they will resort to the next best thing, local search channels. Local channels can provide the required information relatively easily. Non-local communication channels require most effort to get the needed information. Note that our basic argument easily applies to different actors and different contexts other than consumers in a product domain, so that the model proposed here does not need to remain restricted to consumer behaviour, but may instead be applied to the use of search channels in general.
Our model has made specific claims about the relationship between the knowledge base and the search channels used for information gathering by actors confronted with the decision to innovate or not. The use of all three channels grows as the knowledge base increases in size. Actors with a small knowledge base have insufficient knowledge to evaluate new technologies or information on the basis of their own experience. Therefore they turn to the local search channels. At a certain critical point the actors' knowledge base has grown so large that the local information channels do not provide enough interesting new information anymore. The use of local channels declines, but the importance of non-local channels and the own experience continues to grow. These claims were confirmed in our empirical tests (hypotheses 1-3)
There comes a time when even non-local search channels do not provide the required information anymore compared to the effort put into the search. In this case the actor is really at the 'edge of technology', in which he can only trust his own experience. The relationship between search channels and the size of the knowledge base is graphically displayed in Figure 3. Although the horizontal axis of the graph goes to infinity there is likely to be a point at which the cognitive capacities will start to play a limiting role on the size of the knowledge base (no one possesses infinite knowledge, except for God perhaps).

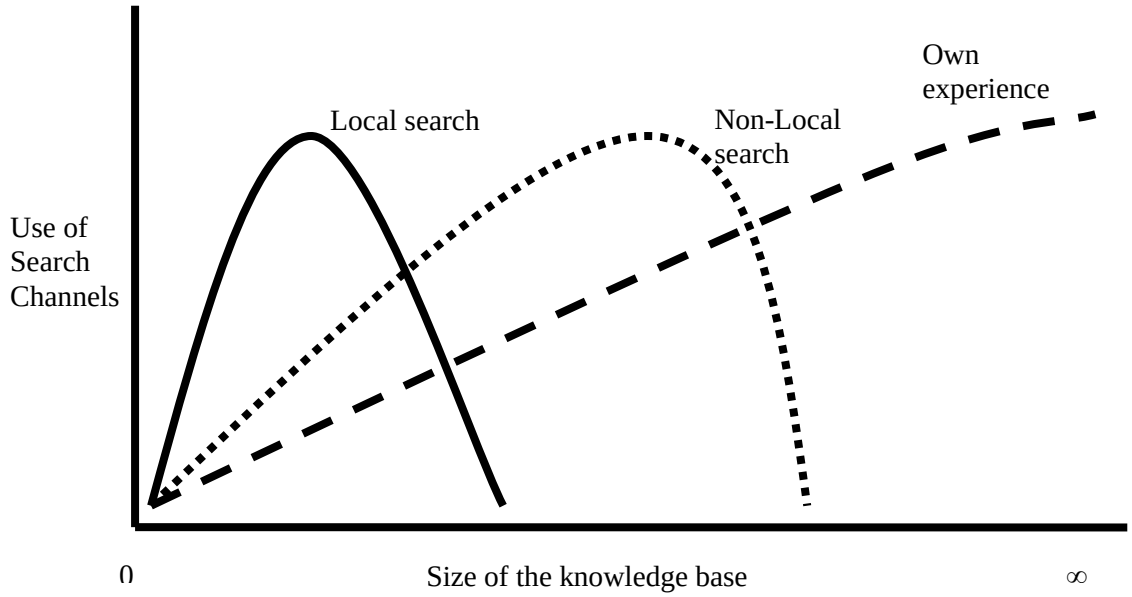

Figure 3: A graphical display of the relationships between the size of the knowledge base and the use of channels for information search.

The confirmation of hypothesis 4 is important, because it provides the relationships behind hypotheses 1 to 3 with a driving mechanism; having a larger knowledge base leads to a larger intention to buy new products. The relationship between the knowledge and the intention to buy new products, mediated by the search channels which thus provide a potential feedback mechanism. If the behavioural intentions are indeed put into action, the actor will increase his knowledge base up to the moment when he is unable to absorb any more knowledge. As predicted this relationship was (partly) mediated by the search channels. The use of local search channels does not influence the intention to buy new products. This could mean that in the case of consumer electronics local-communication (like family or peers) channels are not decisive in establishing a subjective norm that can influence the intention to buy new products. In this case this subjective norm comes from non-local search channels like the internet, and mass media. We do not believe that this is a general finding, but rather a domain specific one. Further tests of our model shall provide more reliable measures of the validity of these findings.

A direct practical implication of this research is that advertisers should send information tailored to the size of the knowledge base through the non-local channels. If they want to target the low-knowledge audience directly they should lower the search-costs for required reliable information significantly below the level of local search costs. This will trigger a switch to those communication channels; the internet can provide an important contribution here.

Our theory predicts that actors with a small knowledge base will be inclined to seek new information through local search channels. The switch from a local channel to a non-local channel is determined by the size of the knowledge base and the costs of finding the required information. Important hereby is to find out what exactly determines the search costs in the specific situation.

The integration of organization level innovation theories (knowledge based view, evolutionary economics) with consumer learning theories has given us valuable new insights on the relationship between the existing knowledge base and the search for information. We were able to develop a general model that need not only be applicable for consumers, but also for other types of actors. These ideas have to be studied further in the future. First of all we suggest looking at other product domains, or at other settings to validate the results. Also looking at the types of information searched for can reveal interesting results. We also

recommend in future studies to asses the internet as a search channel in its own right, because the search costs associated with internet are lower than conventional channels (Bakos, 1997; Dellacoras, 2003) Finally, so far we have looked at a model that only considers the demand side of information; taking into account the supply side of information (e.g. opinion leaders) might also complement our understanding of information search processes.

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Appendix: The measurement models of the Y-variables and the X-variables.

Search channels	(Lambda-Y)	Error variance-covariance (Theta Epsilon)								
Indicator	Estimate	1	2	3	4	5	6	7	8	9
1	1.00									
2	1.00		1.73**							
3	1.02**			1.40**						
4	1.03**		-0.64**	-0.51**	-0.57**					
5	1.00					0.78**				
6	1.20**					0.17**	1.74**			
7	1.02**					0.17**	0.45**	1.19**		
8	0.39**							0.02**	0.17**	
9	1.98**									1.13**

The measurement model and error variance covariance table for search channels. *: $p < 0.05$; **: $p < 0.01$. Indicator 1 is a single indicator variable for own experience with no measurement error assumed, indicators 2 and 5 are reference indicators for local and non-local search channels

Intention	(Lambda-Y)	Error variance-covariance (Theta Epsilon)							
Indicator	Estimate	1	2	3	4	5	6	7	8
1	2.02**	0.67**							
2	1.93**		0.70**						
3	1.55**			0.80**					
4	1.69**		0.43**		0.77**				
5	1.69**					0.77**			
6	1.83**						0.73**		
7	0.62**						0.13**	0.97**	
8	1.45**					-0.16**		0.15**	0.83**
9	1.54**		0.21**		0.17**				
10	1.00							0.21**	
11	0.48**							0.27**	
12	0.09**					0.16**	0.18**	0.14**	
13	0.57**				-0.08**		0.16**	0.19**	
14	-1.12**		0.20**		0.23**		0.21**		0.17**
15	-1.54**	0.24**	0.21**	-0.58**	-0.03	0.23**	0.45**	0.11**	0.18**

Intention (continued): Error variance-covariance (Theta Epsilon)							
Indicator	9	10	11	12	13	14	15
1							
2							
3							
4							
5							
6							
7							
8							
9	0.83**						
10		0.92**					
11		0.21**	0.98**				
12		0.24**	0.23**	1.00**			
13			0.17**	0.40**	0.97**		
14	0.36**		0.31**	0.29**	0.34**	0.90**	
15	0.30**	0.43**	0.27**	0.43**	0.43**	0.28**	0.81**

The measurement model and error variance covariance table for the intention to adopt new innovations. *: $p < 0.05$; **: $p < 0.01$. Indicator 10 is the reference indicator.

Knowledge base	(Lambda-Y)	Error variance-covariance (Theta Epsilon)					
Indicator	Estimate	1	2	3	4	5	6
1	1.00	0.51**					
2	1.10**		0.64**				
3	1.08**			0.65**			
4	0.88**				0.43**		
5	0.87**					0.49**	
6	0.90						0.41

The measurement model and error variance covariance table for knowledge base. *: $p < 0.05$; **: $p < 0.01$. Indicator 1 is the reference indicator for knowledge base. Indicator 6 is the single indicator for the quadratic of knowledge base, with 0.41 error variance.