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DIEDERICK VAN THIEL | W. FRED VAN RAAIJ

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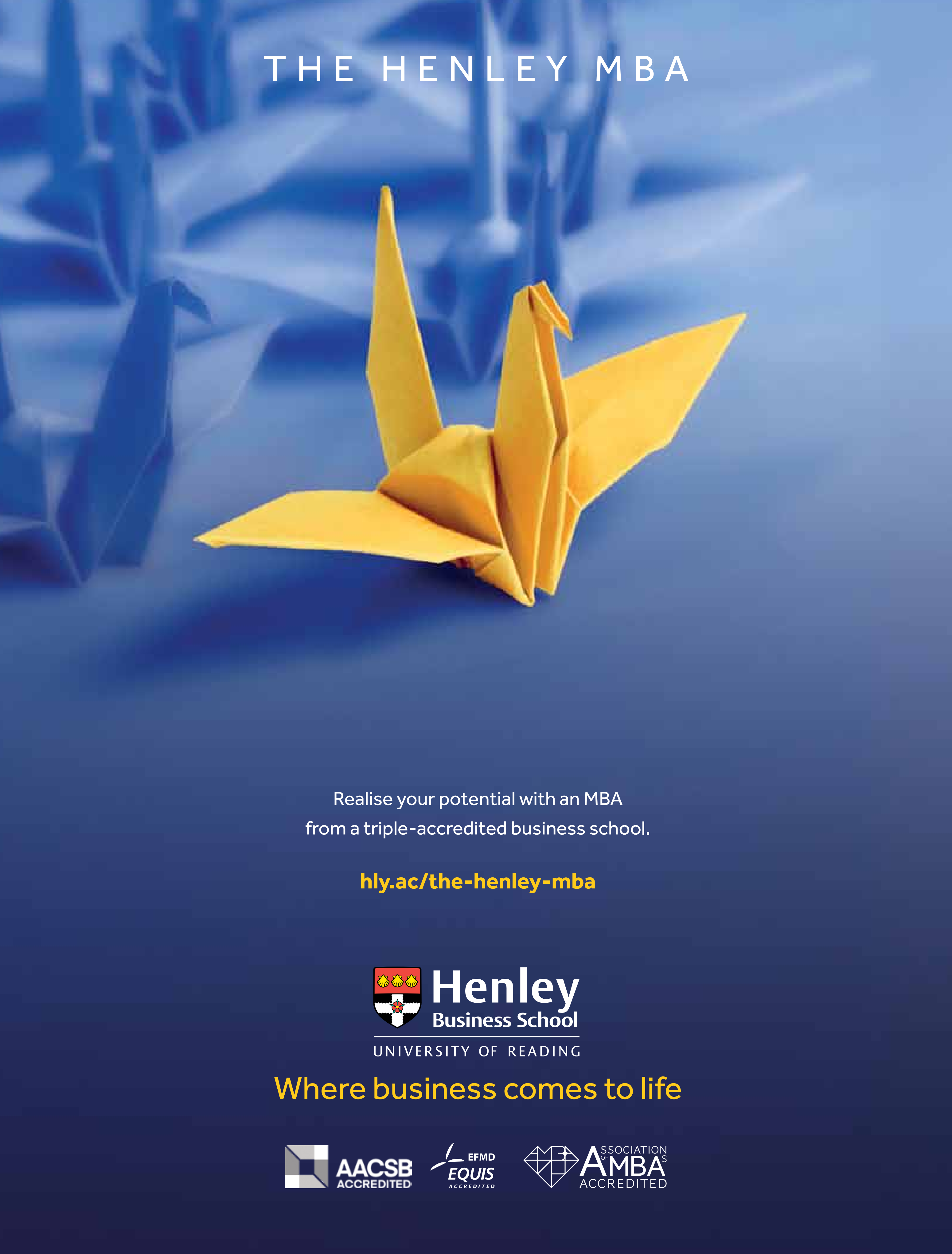
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Targeting the robo-advice customer: The development of a psychographic segmentation model for financial advice robots

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ABSTRACT

The purpose of this study is to develop the world's first psychographic market segmentation model that supports personalization, customer education, customer activation, and customer engagement strategies with financial advice robots. As traditional segmentation models in consumer finance primarily focus on externally observed demographics or economic criteria such as profession, age, income, or wealth, post-hoc psychographic segmentation further supports personalization in the digital advisor's service delivery. It might also provide insight into how to include the 4.5 billion underserved people financially and support inexperienced millennials in securing their future financially. To develop the psychographic segmentation, a survey (N= 2,232) has been conducted across the U.K. and the Netherlands. Factor analysis has been performed to define the following psychographic factors: "convenience," "financial illiteracy," and "rigid personality." Based on these factors, a Ward cluster analysis has been performed to define the psychographic segments across the two markets.

1. INTRODUCTION: THE MARKET OF ROBO-ADVICE

Financial advice is vital for many consumers, as general financial literacy is limited [Van Raaij (2016)]. Financial advice is defined as third-party services that help consumers reach financial decisions [Collins (2010)]. Advice can usually be provided through face-to-face contact, by phone, or digitally. Because today's consumers are asked to make more financial decisions than ever before, as well as the fact that they live in an increasingly complex environment, financial advice is becoming increasingly important [ASIC (2010)]. Financial decision-making, and thus, traditional financial advice, is being transformed by digitalization [Malhotra and Malhotra (2006)]. Younger generations, in particular, specifically millennials, embrace digital lifestyles [PWC (2014)], and such lifestyles have driven the digitization of financial services and the use of financial tools facilitating financial decision-making. As consumers are becoming more and more self-directed, financial capability building is becoming increasingly digital [Van Thiel and Van Raaij (2017)].

Indeed, intelligent agents can be very useful; they are low cost financial assistants [Van Thiel et al. (2008)]. Robo-advisors, intelligent agents, financial assistants, and many other digital decision support systems have the potential to support sound financial decision-making and to reduce financial stress, and thus improve financial security. The ultra-low costs in which these digital advisors can offer their services significantly enlarges the global reach of financial advice. The gap they close is well defined by researchers across the globe. According to the National Financial Capability Study [FINRA (2012)], only 50% of Americans obtained some form of financial advice over a five-year period. According to ASIC, fewer than 40% of the Australian adult population has ever used a financial planner [ASIC (2010)], and in developing countries access to financial advice is even worse. According to the World Bank, 2 billion people lack access to financial services [World Bank (2015)], and many lack access to financial advice to facilitate sound financial decision-making.

Currently, across many geographies, an increasing number of financial service providers are considering the use of robo-advisors: online advice platforms that provide advice by using complex algorithms [Bradbury (2014)]. AT Kearny predicts robo-wealth advisors will manage U.S.$2.2 trillion in assets by 2020 because of the fast-growing adoption rate of this model among younger generations [Van Thiel and Van Raaij (2017)]. The Financial Times estimates that the market for funds advised by hybrid-robo-human services will grow to U.S$16.3 trillion by 2025. Additionally, the growth of the credit-side of the market growth is clear; the global automated peer-2-peer lending market is expected to grow from U.S.$64 billion in 2015 to U.S.$897 billion by 2024 [Transparency Research (2016)].

As the digital lifestyles are becoming commonplace around the world, people are producing an increasing amount of behavioral data. Robo-advisors make use of this and apply algorithms that match consumers or small businesses with financial products or portfolios. As brands increasingly compete on understanding customer DNA at every touch point, behavioral data from all kinds of sources can form the game changers in financial services. Big behavioral data analytics is being applied to find hidden patterns and correlations to more deeply understand customers' behaviors. These deep customer DNA insights can drive personalized and predictive services. Personalization and predictive services are, especially in relation to personal finance and financial planning, services that can facilitate sound financial decision-making across populations.

> "Five million jobs will be lost by 2020 as AI, robotics, nanotechnology and social economic factors replace the need for human workers."
>
> World Economic Forum, Future of Jobs Report, 2016

The increasing number of behavioral data driven services forecast the strong growth of robo-advisors, intelligent agents, and virtual assistants in the coming decades. The University of Oxford places financial advisors on their list of the "Top five jobs that robots are already taking" [Frey and Osborne (2015)]. Frey and Osborne's research indicates that financial analysts and advisors are being replaced by robo-advisors, driven by predictive systems, big data, and computing power. Robo-advice is swiftly growing because of the increasing self-directedness of people; the full potential of robo-advice can only be reached by larger adoption.

The change in customer-need structures through the increasing impact millennials have, as well as the introduction of modern technologies such as digital and robo-advice, increases the need for more personalized segmentation models. The objective of this research is to develop the world's first psychographic segmentation model that uncovers and monitors the elements that motivate consumers to make use of digital or robo-advice. Psychographic segmentation is an approach to financial advice market segmentation based on the personality characteristics of consumers. Banks can apply it in more personalized strategies for increasing customer engagement and lowering the cost of acquisition and servicing. In this study on financial advice, we focus on one of the most complex forms: mortgage advice. Also, to validate the model, research has been conducted in Europe's two most advanced mortgage advice markets: the U.K. and the Netherlands. The segmentation model provides insight into psychographic factors and variables that drive perceived satisfaction with financial advice robots and can be applied in advanced marketing and risk strategies.

2. FROM CONSUMER SEGMENTATION TO PERSONALIZATION

2.1 Financial advice and customer segmentation models

Product differentiation and market segmentation are marketing strategies aimed at increasing engagement with customers. Product differentiation refers to the differentiation in the product perception due to physical and non-physical attributes, including price, to better meet human expectations [Dickson ad Ginter (1987)]. In imperfect market situations, in occasions where there is no homogeneity for all competitors in the market, market segmentation is another commonly used strategy [Smith (1956)]. Smith illustrated that market segmentation involves viewing a heterogeneous market as several smaller homogeneous markets. Smith suggested three criteria to be fulfilled in segmentation: (1) homogeneity (i.e., communality needs within groups); (2) distinction (i.e., uniqueness between groups); and, (3) reaction (i.e., similarity of response toward marketing strategy, product, offer, or services within a group).

Market segmentation and product differentiation are two sides of the same coin. The link between product differentiation and market segmentation is the product benefit [Van Raaij and Verhallen (1994)]. Market segmentation is also defined as a recognition of the existence of multiple demand functions and the development of a plan to meet one or more of these functions [Frank et al. (1972)]. These groups can be addressed by specially designed, but also standardized, strategies [Kotler & Cox (1980)]. Kotler (1980) claims that market segmentation creates a more finely tuned product or service, offering a price appropriate for the target segment. Kotler (1980) also claims that three major segmentation forms are commonly used: demographic, psychographic, and behavioral [Andreasen et al. (2003)]. Customer segmentation by banks, however, remains largely limited to categories of corporate and retail customers, as traditionally defined [Machauer and Morgner (2001)]. Corporate customers are distinguished by their geographic range of activities, sector, and size. In personal retail banking, externally observed demographic or economic criteria, such as profession, age, income, or wealth are often the preferred dimensions for segmentation [Moutinho and Meidan (1984), Harrison (1994)]. However, demographic and economic criteria are rough indicators for the need structures and the reaction patterns of retail customers [Machauer and Morgner (2001)].

These forms of traditional market segmentation are bound to a high probability that standardized service packages are offered to customers that are not suitable. Thus, low satisfaction and possible migration of customers is to be expected [Machauer and Morgner (2001)]. As segmentation can be forward, backward, and simultaneous [Van Raaij and Verhallen (1994)], modern forms of segmentation are post-hoc. Backward or reverse segmentation means dividing customers into need clusters based on the data a company already has. Thus, a heterogeneous population is surveyed and segments are determined based on homogeneous response patterns from within the population [Machauer and Morgner (2001)]. The research seeks measures that cluster consumers into potentially profitable but unique groups within the population. Some studies in this area use customer responses related to questions on product features or usage. Product usage frequency patterns [Burnett and Chonko (1984)], for example, identified four customer segments for packaging banking products. Accordingly, the segment labels "traditional," "convenience," "investment," and "debt" were derived from the characteristics of the preferred products within these segments.

2.2 Psychographic segmentation

Several other studies using post-hoc segmentation approaches are oriented toward the psychological determinants of customers, in that they refer to psychographic or benefit segmentation [Machauer and Morgner (2001)]. The purpose of psychographics is to obtain a better understanding of the consumer as a person by measuring psychological dimensions, way of living, interests, and opinions [Ziff (1971)]. The most widely used approach to measure lifestyle is by using activities, interests, and opinion (AIO) rating statements [Plummer (1974)]. A widely used tool for lifestyle segmentation is the VALS scheme [Rokeach (1973)], which blends research of values, hierarchy of needs, and sociology in its operation. Another frequently used tool for lifestyle segmentation is the "list of values" [Kahle et al. (1986)].

In this era, where millennials force their digital lifestyles onto markets and technologies such as machine learning bring enhanced analytic possibilities, big data-based segmentation revolutionizes opportunities for personalized targeting. As, for example, segmentation for mobile devices is typically based on demographics and reported use, smartphone measurement software enables us to directly add observed user behavior and psychographics [Hamka et al. (2014)]. Big data insight is generated through analytics, which can be subdivided into descriptive analytics (analytics activities that explain the past), predictive analytics that predict/forecast future outcomes, and prescriptive analytics, which predict future outcomes and suggest options for decision-making. In the last step of the "virtual value chain," the data or insight might be visually represented, the data distributed, or access to the data or analytics results provided, for example, through an API [Hartmann et al. (2014)].

Hypothesis 1: For defining digital or robo financial advice market segments, psychographic segmentation can be applied for developing personalized robo-advice strategies.

2.3 Financial advice and financial literacy

On the demand side of robo and digital financial advice, the issue in the global financial advice markets is that financial advice is being perceived as inaccessible. The National Financial Capability Study [FINRA (2012)] conducted a survey among U.S. citizens (n=1488) to discover the number who obtained some form of financial advice in the past five years and found that 57% had. 8% had received advice on debt management, 21% on tax planning, 24% on receiving a loan, 33% on investments, and 33% on insurance.

Furthermore, the survey showed that a higher income, good education, and sound financial literacy led to more financial advice being sought. Also, the generation of millennials are approaching their peak buying years [Goldman Sachs (2017)]. According to Goldman Sachs this generation is on their way to marry, buy cars and houses for their family life. PWC studies the financial literacy of millennials [PWC (2015)] and found that millennials struggle with their financial lives. Only 24% have adequate financial knowledge, 34% are very dissatisfied with their current financial situation, but still only 27% seek professional financial advice on saving and investment. They are inexperienced financially and also embrace a digital lifestyle, thus new financial technology such as financial advice robots can fill this knowledge gap.

Hypothesis 2: Financial illiteracy is a differentiating factor in the psychographic segmentation model for developing personalized robo-advice strategies.

2.4 Financial advice and motivation

FINRA (2012) found that people's level of financial literacy and education impacts their openness to financial advice. PWC research illustrates that only 27% of millennials use financial advice. Motivation to use digital financial advice, therefore, is a potential factor that differentiates customer segments for building personalized robo-advice strategies. To be motivated means to be moved to do something;

motivation concerns energy, direction, persistence, and equifinality; all aspects of activation and intention [Deci and Ryan (2010)]. Consequently, a person who feels no impetus or inspiration to act is characterized as unmotivated, whereas someone who is energized or activated toward a goal is motivated. People do not only have different degrees of motivation, but also various kinds of motivations. The orientation of motivation concerns the underlying attitudes and goals that give rise to action [Deci and Ryan (2010)]. In their "self-determination theory," Ryan and Deci distinguish several types of motivation based on various reasons or goals that give rise to an action. Whereas intrinsic motivation refers to doing something because it is inherently interesting or enjoyable, extrinsic motivation refers to doing something as a means to reach another goal or outcome.

Hypothesis 3: Motivation is a differentiating factor in the psychographic segmentation model to develop personalized robo-advice strategies.

2.5 Financial advice and risk appetite

Nelson (1970) classifies products into search and experience goods. Search goods offer consumers the ability to obtain product quality information prior to purchase, whereas experience goods, like financial advice, do not. Credence goods are a specific category of experience goods. Wolinsky (1995) defines credence goods as experience goods whose sellers are also experts who determine customers' needs. Information asymmetry in credence goods markets lead to prices that embody mark-ups over costs. Furthermore, the equilibrium does not maximize expected customers' surplus. Another consequence of information asymmetry in credence goods is fraud [Wolinsky (1995), Emons (1997)]. Since customers can never be certain about the quality of the sellers' services, experts have opportunities and incentives to cheat. Consequently, regulators force financial advisors to investigate the risk profile of a customer and match their advice. Due to the 2008 economic crisis, trustworthy assessments of risk perception and risk tolerance of financial customers became a central element in financial supervision [Roszkowsky and Davey (2010)]. To differentiate between risk tolerance and risk perception, we must first define risk. According to Roszkowsky and Davey, risk is the uncertainty that exists as to what the eventual outcome will be. Risk arises in any decision where there is some doubt about at least one of the possible outcomes. The risk inherent in any given situation will depend on the range of possible outcomes and the likelihood and value of each outcome. Thus, in a financial context, risk tolerance is the amount of risk an individual chooses when making a financial decision. Although risk tolerance is largely a fixed personality trait and stable, it is nonetheless marginally subject to situational influences (for example mood) and may change due to life circumstances (for example aging).

Furthermore, an evaluation of the degree of risk generally involves a perception of the situation, which means that there is some interpretation of the objective reality. Tversky and Kahneman (1974) show that risk perception is a function of intuitive notions of risk (e.g., probability of loss and loss aversion) rather than of technical risk measures such as beta, standard deviation, or variance.

Hypothesis 4: Risk tolerance is a differentiating factor in the psychographic segmentation model to develop personalized robo-advice strategies.

2.6 Purpose of this research

As defined in the introduction, the purpose of this study is to develop the world's first psychographic market segmentation model that supports personalization, customer education, customer activation, and customer engagement strategies with financial advice robots. As traditional segmentation models in consumer finance primarily focus on externally observed demographics or economic criteria such as profession, age, income, or wealth [Meidan (1984), Harrison (1994)], post-hoc psychographic segmentation might support further personalization in financial advice robot service delivery. It might furthermore provide insight on how to include the 4.5 billion underserved people financially and support inexperienced millennials with building financially stable lives.

3. METHODOLOGY AND RESULTS

3.1 Developing the "digital psychographic segmentation" (DPS) model

3.1.1 DEVELOPING A CONCEPTUAL MODEL AND SURVEY DESIGN

Firstly, the main psychographic dimensions were determined. These psychographic dimensions served as the conceptual basis for a questionnaire (which is explained in the following section) that aimed to gain evaluations from digital mortgage advice customers of their psychographic profile and their perceived acceptation of digital financial advice. Based on earlier scholarly research [Machauer and Morgner (2001), FINRA (2009), Deci and Ryan (2010), Tversky and Kahneman (1975)], AFM field studies [Van Raaij (2016)], and several brainstorming sessions among academic peers, the variables for psychographic segmentation have been defined.

The survey confirmed the importance of the following variables:

1. Need for relevant information
2. Time spent on finding relevant information
3. Span of alternatives evaluated in the decision process
4. Support being asked for in the information search
5. Level of trust in financial advisors
6. Openness to new products and services
7. Rationality in the buying decision
8. Level of financial knowledge
9. Level of following financial market developments
10. Risk appetite
11. Level of maximization in the buying decision
12. Level of "social opinions" applied in buying decision

The psychological profiles composed of these variables should characterize the way a person is open to digital financial advice. It should provide an input to digital and robo-advice leadership teams on how to design digital advice strategies and personalized services per customer segment.

Based on the variables, a survey was composed in close cooperation with research agency, GfK. The survey design consisted of five sections with 38 questions on satisfaction with attributes of the advisor and the advice service quality. Section A contained screening questions to build a social-demographic profile of the respondents. Section B contained questions on the performance evaluation of recent mortgage closings. Respondents were asked to rank their experience with the performance on the variable list of their most important financial advisor. To measure latent constructs such as opinions and interests, scoring took place on a 7-point Likert-scale. Section C contained questions for benefit evaluation on the variable list of mortgage closings. Again, scoring took place on a 7-point Likert-scale. These sections were applied in composing the DCX-model [Van Thiel and Van Raaij (2017)]. Sections D and E contained statements about respondents' psychographics. To measure the latent construct of financial behavior, the responses were also measured on a 7-point Likert scale. For this paper on psychographic segmentation, Section E and the response in Section A are used. The survey was validated on a pilot group of 100 respondents prior to the larger online field experiment.

> "85% of millennials prefer using robo-advisors over traditional advisors"
>
> Charles Schwab, 2017

3.1.2 PERFORMING THE SURVEY

To develop and test the model, an online survey of 2,332 consumers was conducted across two experiments. Respondents were grouped based on their recent experience with buying a house and choosing a mortgage. The respondents were randomly selected from the GfK-consumer panels of the U.K. and the Netherlands and divided into two groups (1) 2013 the Netherlands (n=1407); and (2) 2013 The U.K. (n=935). The first online survey experiment was held in Q1-2013 in the Netherlands (n=1407). In the experiment, experienced financial advice users (N=815) were differentiated from the inexperienced users (n=592). The second experiment was held in Q4-2013 in the U.K. (n=935). Because the differentiation between experienced and inexperienced users in the first experiment created no significant insights, the respondents in this experiment were only experienced advice users (consumers who had received mortgage advice in the last year). To be able to compare the results over the experiments, the same questionnaires and analyses were applied. The experiments were used to develop and validate the DPS model.

3.1.3 PSYCHOGRAPHIC SEGMENTATION

On the survey response, principal component factor analysis with Varimax rotation was applied with the 12 psychographic variables. The Varimax rotation with Kaiser normalization was performed over four rotations. Both in the U.K. as in the Netherlands, three components (convenience with eigenvalue of 1.89; financial illiteracy with eigenvalue of 1, and rigidity with eigenvalue of

0.51) resulted from the principal component analysis. Based on the Kaiser criterium that eigenvalues >1 should be selected, only convenience and financial illiteracy should be components in the psychographic model. However, based on the importance of risk appetite and emotionality in decision-making according to regulators, a third component "rigidity" is added to the model. The rotated component matrix for the U.K. is shown in Table 1 and for the Netherlands in Table 2.

With the components discovered, a Ward's minimum variance clustering model was applied to classify financial advice consumers. Based on the three components, four dominant segments were obtained explaining psychographic differences in suitability for digital financial advice. The following decision rules were applied to assign to each cluster:

1. Explained variance
2. Group size >100
3. Interpretation of homogeneity of the groups
4. If no clear interpretation, start at rule 1

Table 1: Rotated component analysis U.K.

	ROTATED COMPONENT MATRIX[a]			
	COMPONENT			
	CONVENIENCE		FINANCIAL ILLITERACY	RIGID
Information: Seek a lot – Try to limit	e18_1	.800		
Time: Take all I need – As quickly as possible	e18_2	.737		
Alternatives: Many – Limited amount	e18_3	.801		
Research: All myself – Let others do as much as possible	e18_4	.646		
Trust advisors: Easily – Do not	e18_5			.671
Products: Try new – Stick to known	e18_6	.407		.468
Decisions: Based on feelings – Logically and systematically	e18_7			.747
Financial knowledge: A great deal – Very little	e18_8		.832	
Financial market developments: Fully abreast – Barely follow	e18_9		.834	
Risks: Fully prepared to take – Averse (maximum security)	e18_10		.598	.453
Product search: Until the best possible – As soon as found	e18_11	.826		
Comparitive shopping (usage rating & reviews websites): Use a lot – Do not use	e18_12	.628		

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in four iterations.

Table 2: Rotated component analysis the Netherlands

	ROTATED COMPONENT MATRIX[a]			
	COMPONENT			
	CONVENIENCE		FINANCIAL ILLITERACY	RIGID
Information: Seek a lot – Try to limit	e18_1	.830		
Time: Take all I need – As quickly as possible	e18_2	.776		
Alternatives: Many – Limited amount	e18_3	.701		
Research: All myself – Let others do as much as possible	e18_4	.642	.420	
Trust advisors: Easily – Do not	e18_5		-.464	.394
Products: Try new – Stick to known	e18_6			.719
Decisions: Based on feelings – Logically and systematically	e18_7			.645
Financial knowledge: A great deal – Very little	e18_8		.780	
Financial market developments: Fully abreast – Barely follow	e18_9		.726	
Risks: Fully prepared to take – Averse (maximum security)	e18_10		.401	.677
Product search: Until the best possible – As soon as found	e18_11	.808		
Comparitive shopping (usage rating & reviews websites): Use a lot – Do not use	e18_12	.628		.357

Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalization.
a Rotation converged in four iterations.

Table 3: U.K. psychographic segments and means

		F1: CONVENIENCE	F2 FINANCIAL ILLITERACY	F3 RIGID
		MEAN		
WARD METHOD	C1 Convenience	1.56149	-.05108	.09060
	C2 Trustful with knowledge	-.26301	-.90491	-.84376
	C3 Rigid	-.44974	-.33342	1.03366
	C4 No financial knowledge	-.28716	.83885	-.40067

Table 4: The Netherlands psychographic segments and means

	CONVENIENCE	TRUSTFUL WITH KNOWLEDGE	RIGID	NO FINANCIAL KNOWLEDGE
	1	2	3	4
	MEAN	MEAN	MEAN	MEAN
Convenience	1.6	-0.3	-0.4	-0.3
Financial illiteracy	-0.1	-0.9	-0.3	0.8
Rigid	0.1	-0.8	1.0	-0.4

The dominant psychographic segments and their means are displayed in Tables 3 and 4.

The validation approach for the discovered psychographic segments was in performing this study across Europe's two foremost mortgage advice markets: The U.K. and the Netherlands. The U.K. and the Netherlands are understood as front-runners because of their advanced financial advice eco-systems (financial advisors, governmental regulation, and fintech industry).

3.2 The DPS-model and its validation in two markets

3.2.1 DIGITAL PSYCHOGRAPHIC SEGMENTATION IN THE NETHERLANDS

The principal component analysis in the first experiment shows the factors and their variables across the experienced and inexperienced customer groups through the surveys in the U.K. and the Netherlands that point toward similar factors for psychographic segmentation in digital financial advice. This supports the explanation of the cross-cultural expectations of digital financial advice. The factors are (1) need for convenience, (2) level of financial literacy, and (3) need for rigidity. The DPS-model is presented in Figure 1.

Although the inexperienced and experienced people show great similarities, the factor impact differs across both customer groups. Inexperienced people give more importance to trust in advisors (24.7%) and process rigidity (18.4%), whereas experienced people give more importance to financial knowledge (34.2%).

Applying the factors in a Ward cluster analysis yielded a 4-segment psychographic model. For defining the psychographic profiles, the answers in Section E of the questionnaire were merged with Sections A, B, and C. The profiles designed are: (1) convenience seekers; (2) trustful with knowledge, (3) rigid, and, (4) financially ignorant (no financial knowledge). The psychographic segments are shown in Figure 2.

Convenience seekers score high on (1) trying to limit information search (.830), (2) buying the product as soon as one is found (.808), (3) buying the mortgage as quickly as possible (0.776), (4) evaluating limited alternatives (.701), and (5) letting others do the research (.642).

Rigid people are more conservative mortgage buyers. They do not trust advisors very much (.394), tend to stick to known products and brands (.719), decide logically and systemically (.645), and are risk-averse (.677).

On the knowledge factor, differentiation is seen in the segments "trustful with knowledge" with high scores on financial knowledge (.780) and financial market developments (.726). The knowledge aspect makes this segment progressive, showing a willingness to spend time on finding relevant information and the best product for their needs. The customer segment "financially ignorant" instead spends no time on financial decision-making. They, therefore, tend to be neutral and follow financial advice.

Figure 1: Digital psychographic segmentation model

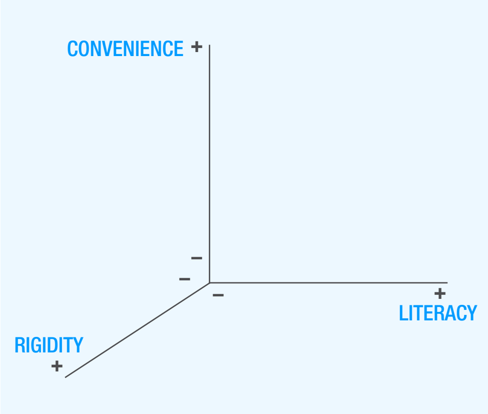
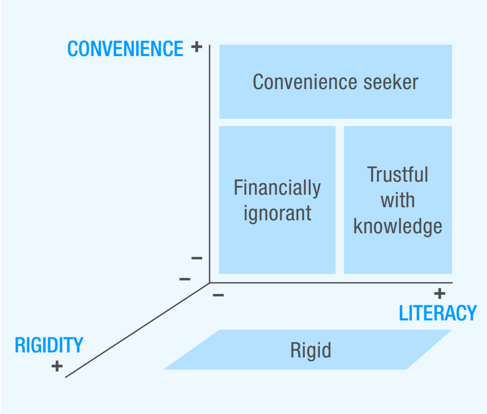


Figure 2: Digital psychographic consumer segments



3.2.2 DPS IN THE U.K.

Although the second experiment (U.K.) also shows the same psychographic factors segmenting the market, their impact differs from the Dutch market. Financial knowledge (34.1%) is the most important variable. But rigidity (28.1%) is important for the British. Convenience (17.1%), on the other hand, is less important in the U.K. Applying the factors in a Ward cluster analysis led to a three-segment psychographic model. The British psychographic customer segments resulting from the Ward-analyses are: (1) convenience seekers, (2) the financially illiterate, and (3) rigid consumers.

As in the Netherlands, British convenience seekers score high on (1) trying to limit information search (.800), (2) buying the product as soon a one is found (.826), (3) buying the mortgage as quickly as possible (0.737), (4) evaluating limited alternatives (.801), and (5) let others do the research (.646). Different from the Dutch, British convenience seekers do look at comparative shopping instruments such as ratings and reviews (.628).

Rigid people are more conservative mortgage buyers. They do not trust advisors very much (.671) and decide logically and systemically (.747) They are less loyal than the Dutch mortgage buyers in their intention to remain loyal to known products and brands (.468).

The financially illiterate group are the third psychographic segment in the British market with low financial knowledge (.832), low financial market knowledge (.834), and are looking for financial security (.598).

3.2.3 HYPOTHESIS TESTING FOR MODEL INTEGRATION

Hypothesis 1: For defining digital or robo financial advice market segments, psychographic segmentation can be applied for developing personalized robo-advice strategies.

The principal component analysis with Varimax rotation showed three factors that differentiate in psychographic mortgage advice segments. The factors are convenience (eigenvalue of 1.89), financial illiteracy (eigenvalue of 1), and rigidity (eigenvalue of 0.51). Based on the Kaiser criterium that eigenvalues >1 should be selected, only convenience and financial illiteracy should be components of the psychographic model. Consequently, Hypothesis 1 can be validated.

Hypothesis 2: Financial illiteracy is a differentiating factor in the psychographic segmentation model for developing personalized robo-advice strategies.

The principal component analysis with Varimax rotation showed that financial illiteracy is a differentiating factor in psychographic advice segmentation. The eigenvalue of 1 is good enough to select financial illiteracy as a factor. Financial illiterates in the U.K. have low financial knowledge (.832), low financial market knowledge (.834), and are looking for financial security (.598). In the Dutch market, financial illiterates have low financial knowledge (.780) and financial market knowledge (.726). Also, the study in the Dutch market revealed a fourth segment "trustful with knowledge." They are the most progressive customer segment and spend a lot of time finding the best solution matching their needs. Financial (il)literacy is a differentiating factor in psychographic customer segmentation. Hence, the second hypothesis can also be validated.

Hypothesis 3: Motivation is a differentiating factor in the psychographic segmentation model to develop personalized robo-advice strategies.

The principal component analysis did not show motivation as a differentiating psychographic factor. Nevertheless, in the factor, scores differentiating between people who actively seek relevant information, spend time and keep searching until they find the best solution for their needs show high loadings. These people are segmented in the U.K. in the psychographic segment of the "rigids." In the Netherlands, they are segmented in the psychographic segment of "trustful with knowledge." Hence, although not a factor in the model, someone's personal motivation is something to consider when developing digital strategies. Thus, Hypothesis 3 cannot be validated.

Hypothesis 4: Risk tolerance is a differentiating factor in the psychographic segmentation model to build personalized robo-advice strategies.

The principal component analysis did not show risk tolerance as a differentiating psychographic factor. The influence of risk tolerance in the U.K. is seen in the customer segment of the financially illiterate who seek maximum security. In the Dutch psychographic segmentation risk tolerance also influences the behavior of the financially ignorant who seek maximum security. But also, "trustful with knowledge" with a higher risk tolerance include people that are open for trying new products and services. Nevertheless, Hypothesis 4 cannot be validated.

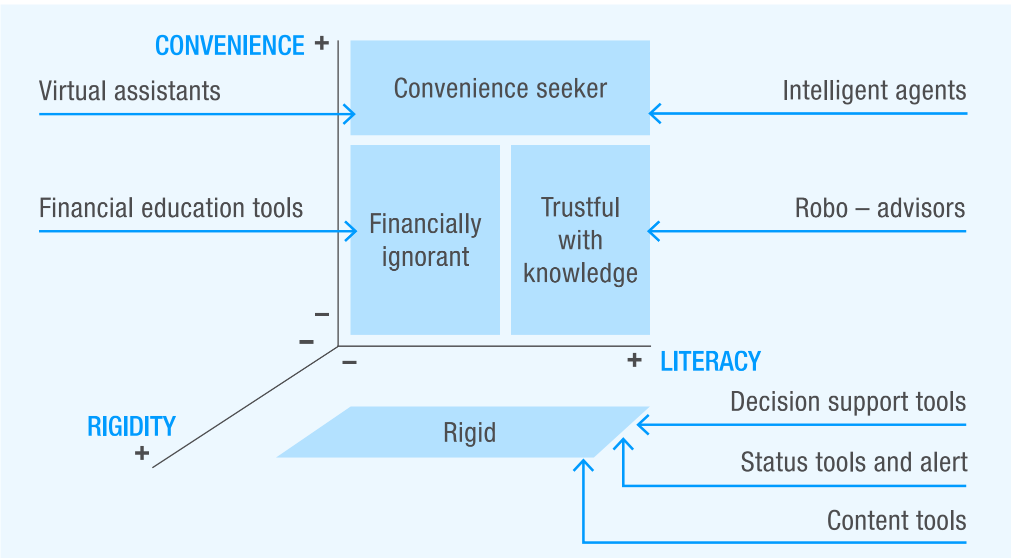
4. DISCUSSION

As defined in the Introduction, the purpose of this study is to develop a world first psychographic market segmentation model that supports personalization, customer education, customer activation, and customer engagement strategies with financial advice robots. As traditional segmentation models in consumer finance primarily focus on externally observed demographics or economic criteria, such as profession, age, income, or wealth [Meidan (1984), Harrison (1994)], this research discovered that post-hoc psychographic segmentation supports further personalization in banking advice services.

The cross-cultural study discovered three differentiating psychographic factors that should always be considered when targeting a market for digital or robo-advice. Convenience appears to be the dominant factor and goes back to the need to buy the best fit product with the lowest effort. Content personalization strategies, as well as predictive, prescriptive, and automated services will appeal to this psychographic segment. When executed well, this segment is approachable for financial intelligent agents and virtual assistants.

Financial illiteracy is the second psychographic factor to consider when targeting a digital advice market. Financial illiteracy is bipolar. Those with low literacy need education and support in their financial decision-making. Their overarching need is to find solutions that provide financial security. The financially ignorant

Figure 3: Digital Psychographic Consumer Targeting



are not the most promising for digital or robo-advice. Nevertheless, digital advisors can support customers in this segment with education, orientation, and transaction tools that underpin their financial decision-making. The financial inclusion of the 4.5 billion globally underserved people is an opportunity to develop these kind of digital education tools.

The other pole is the customers with high financial literacy. Customers in this segment have a high interest in personal finance and market developments. They also tend to spend a lot of time in developing their knowledge and are open to new products and services. Because of their knowledge, they are often role models for their friends and families. This highly literate customer segment is appealing for financial advice robots to approach. In parallel with the convenience segment, content personalization strategies and predictive services will appeal to this segment. Different from the convenience segment, the "trustful with knowledge" customers appreciate additional information like reviews, ratings, and blogs to grow their knowledge.

The third psychographic factor to consider when targeting a market for digital advice is the rigidity of people. Rigid people are conservative in their decision-making and want to be in control. They tend to spend a lot of time on finding the best solution because they do not really trust advisors. This segment seems unappealing for financial advice robots because of the trust element. However, if digital tools like, for example, virtual financial assistants are developed that smartly support information searches and improve financial control, they might want to use them. For digital and robo-advisors a targeting model is presented in Figure 3.

Banks and regulators can apply the DPS-model in their service development or supervision. Banks can apply the DPS-model in personalized tools and treatments to their vulnerable customers. Active servicing strategies to avoid bad payment behavior, but also personalized collection strategies, can be encouraged by the regulators applying the DPS-model. In addition, through smart targeting of customer segments with financial advice robots, DPS provides valuable insights. Convenience seekers and people with high financial knowledge are the preferred target groups. For the financially ignorant with rigid behavior patterns, financial robots should focus on education, insight, and control. Furthermore, based on psychographic segmentation, regulators can validate to what extend banks support a customer's personal decision-making. Are the illiterate customers getting the right educational tools and treatment? Are the rigid customers exposed to the right information and control tools, and are robo-advice solutions providing enough information to support sound financial decision making?

The model can also inspire researchers studying changing consumer needs to improve their contribution to closing the advice gap. Applied research on big data-driven robo-advice, virtual assistants, alternative risk modeling, and emerging forms of data-driven financial education and advice can significantly contribute towards closing the financial advice gap. As of 2012, about 2.5 exabytes of data are created each day, and that number is doubling every 40 months – 90% of global data today was produced in the past two years. More data cross the internet every second than were stored in the entire internet just 20 years ago. Big data is arriving from multiple sources with an alarming velocity, volume, and variety. This data will open new opportunities for financial advice robots to personalize their content and services on the psychographics and behaviors of their customers. New artificial intelligent techniques like machine learning make it possible for digital advisors to apply these unstructured data to personalize customer experiences.

5. LIMITATIONS

There are some limitations to this research that should be considered when interpreting the findings. The new models are derived from research in the U.K. and Dutch markets. Although these markets are known as precursors in digital financial advice, additional geographic-specific research must be conducted to generalize the findings to other global markets.

The data of this research were gathered in the year when both the U.K. and the Dutch governments introduced commission stops on complex financial advice. This has stimulated the growth of online low-cost financial advisors since 2013. Due to the brief period between the introduction of the commission stop and when this research was conducted, the price and accessibility benefits offered by these online financial advisors are still in their infancy. Additional time-series research should be performed to monitor the changing impact of the drivers in the DPS-model.

Finally, this research has been singularly performed on digital mortgage advice. Further research can be conducted to focus on business models such as comparison sites, robo-wealth advisors, and advisors in other service industries such as healthcare and utilities.

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