Openness to Robot Financial Investment Recommendation Systems, among Users of a Hungarian Financial Portal

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Abstract: In this article, we primarily examine the indirect and direct openness to robot recommendation systems based on a Hungarian survey conducted in 2019 on the financial habits of readers of Portfolio.hu (an online economic portal). We briefly introduce the broader theoretical background of our research (financial investment recommendation systems) and the structure of our survey (questionnaire blocks and data collection). Openness to both direct and indirect use (with a human advisor) of robot recommendation systems was asked about and analyzed. Over 1,500 respondents completed our questionnaire, and the connections between robot recommendation systems and other variables e.g., place of residence, age, subscription to digital services, visibility settings in social media and level of savings, were examined. In addition to the simple bivariate analysis, we also carried out a cluster analysis. Our research shows that roughly one in six respondents would be open on their own to a direct robot recommendation, however, many are uncertain, and many would only use the service with the support of human advisors. One of the most important results of our research is that young people, much the same as older people, are not automatically open to a robot recommendation system. Based on our results, it would be constructive to combine hard socio-demographic, digital cultural, and financial factors to create better robot recommendation systems. However, it should be considered that our research was conducted in Hungary with a target group more open to savings and financial investment (hence the research results require further examination).

Keywords: robot recommendation systems; customer openness; financial investment; savings; Hungary

1 Introduction and Theoretical Background

This article deals with a detailed description of the partial results of a broader research project. This broader project aims to increase the intelligence of a financial investment recommendation system by better understanding its target group. In doing so, we identify possible groups of users and identify the dimensions along which the recommendation system can be created. The goal is to use online behavior and attitudes to investment to predict which investment solution is the most suitable for a prospective consumer. In this article, we primarily examine the indirect and direct openness to a robot recommendation system after presenting our methodology with the structure of our research questionnaire below.

Based on Rogers' diffusion theory [1], it can be said that first adoption groups of an innovation (i.e., innovators and early adopters) typically have advanced education, financial liquidity and higher social status. According to Rogers some demographic variables, like age do not play a significant role in diffusion, but other research finds a relationship between them. It is a common belief that young people are much more open to new technologies than older people. Based on the research of Olson and his colleagues [2], there are differences in the diffusion of technologies between young and old age groups, which can primarily be traced back to differences in knowledge. In our research, we refute the popular expectation, and state that young people are not more open to robot recommendation systems, in fact, in many respects, they have the same opinion as the over-65 age group.

Concerning robot recommendation systems, one might think that they will primarily play a worthwhile role only in the future. The truth is that Netflix launched its infamous competition, the Netflix Prize more than 15 years ago, in 2006, which aimed to build a better recommendation system [3]. This prize contributed to the knowledge and appreciation of recommendation systems and helped increase the number of professionals in this field worldwide. Since 2006 robot recommendation systems have played an important part in our lives. For example, we use robot recommendation systems without noticing it when we watch videos on YouTube [4], choose a tourist destination or attraction [5], accept content recommended by the system in a music service, like Spotify or Apple Music [6] [7] or film streaming and movie services [8-10], we filter user generated content [11] or choose from location-based services. [12] Finally, we also heavily rely on recommendations when we buy something in a webshop [13].

The use of robot recommendation systems has a long tradition in the financial field. According to the literature review of Zibriczky [14], diversity is a characteristic of both applied recommendation techniques and financial domains. The most important financial domains include the stock market (predicting prices and giving buy/sell signals, e.g. [15]), asset allocation and portfolio management (but based mainly only on level of risk taking e.g. [16]), banking decision support systems [17], loans and peer-to-peer lending [18], insurance products and policies [19], venture finance and business-plan related questionnaires [20]. From our perspective the most important domain is recommendation systems in personal savings which concentrate on individual attributes and as Zibriczky states only a few papers focus on this topic. Our work is mainly targeted at this niche, i.e., what personal characteristics can be identified as key in openness for robot financial recommendation systems besides the well-known risk-taking habit?

An important wider theoretical context of our research is Digital and Cognitive Corporate Reality (DCR) [21]. This transformative approach integrates digital technologies, artificial intelligence, and cognitive capabilities to redefine corporate management and business operations. The DCR highlights the importance of evolving alongside information and communication technologies and acknowledges the significant impact of advancing AI capabilities. This underscores the need for a fundamental change in how we perceive and approach corporate management and business science. Our research contributes to a deeper comprehension of how the practical implementation of robot recommendation systems in savings advice correlates with customer openness, attitudes and other variables. The findings enable financial organizations to more effectively integrate digital solutions into their business processes concerning financial consulting. Human-AI workflow must be planned for a robot recommendation system's success. Our study contributes the process of determining which aspects of a particular workflow should be carried out by humans, which should be automated with AI, and which should be implemented in a mode supervised by both humans and AI.

The goal of our research was to collaborate in the creation of an automatic recommendation framework. Based on this framework it is planned to make appropriate investment recommendations to the customers based on a subset of data received in a simplified questionnaire completed by future customers. Recommendations are only based on this method without knowing the recorded historical financial transactions of the same customer (a cold-start recommendation). We sought to develop a method, like User-Based Collaborative Filtering (UBCF) or other well-known approaches, for recommendation systems [22].

In UBCF recommendation systems the customers' known historical transaction data are used to formulate a group of neighbors, but in our case, - which is rather a "cold-start" recommendation – only data collected in the questionnaires are used. It could be a pragmatic choice to use customer data collected from social or other sites, but we discarded this approach as being rather unethical and in some cases even illegal. Using customer-level social media data for third-party recommendation systems after the Cambridge Analytica scandal became unacceptable because of ethical concerns [23].

In a real-life investment situation, a customer most probably does not answer more than 8-10 simple questions. Our goal during the research was to identify these simple questions from a set of more complex questions replied to by a sample of potential customers. We analyzed the replies to this deeper set of questions and sought to find characteristic clusters of customers based on the responses to our questionnaire to identify the cluster profiles characterized by variables not used for the clustering.

The scope of this article is limited to dealing only with some results of the research that seem to attract wider interest. The extent to which the potential target group is open to an automated, robot financial investment recommendation system can also be examined using a questionnaire question. In this article, we primarily focus on presenting our findings in this regard.

2 Research Methodology

The complete questionnaire contained the following blocks:

- **Demographic data:** gender, age, income, settlement type, education, the scope of economic activities
- **Participation in digital culture:** ownership of a smartphone, use of mobile internet, e-commerce activities, use of password manager applications, subscription of online cloud or entertainment services, visibility settings in social media
- **Investment block:** risk awareness of different types of investment, how monthly income is spent, risk-bearing capacity, personal investment preferences, ownership of shares, level of activity in monitoring the yields, ownership of government securities, ownership of private investment fund, monitoring the yields of investment funds, preferences in cost and risk awareness in long-term investment, ability to make simple percentage calculations
- **Way-of-living block:** level of savings, how the respondent makes ends meet, characterization of the financial way of living, planned use of savings, type of present savings, owned insurance policies
- **Planning block:** self-evaluation of method, level of planning activities and accomplishments in life, ability to work in teams, self-reward in the event of success, how decisions are made, daily planning, level of control over different events, time-management abilities, planning abilities, working according to plans, holiday planning in advance
- **Connection to financial services:** number of banking services used, customer category at the bank, satisfaction with the banking services,

satisfaction with the online and mobile services, satisfaction with the scope of services, comprehension of bank statements, preference for a bank with online and telephone communication only, preferences for robot advisors in investment, loyalty to banks vs. better digital services, participation in shareholders' general meetings, wish to have a comprehensive unified security information platform, preference for different types of investment advisors, the role of environmental and social awareness in investments, social awareness vs. yield, perceived level of data protection of financial institutions and social sites, intentionally sharing personal financial information with third-party service providers for better service, use of a potential single platform for all financial transactions, knowledge and use of online-only financial service providers.

Questions about the openness of the robot recommendation were addressed in the last block (concerning financial services). In the questionnaire, we asked respondents, measured on a 5-point scale, how open they would be to a recommendation made by a robot. We asked about openness to both direct and indirect use and regarding the latter using a human advisor:

- **Directly:** "I would like to make an investment decision based on a robot's recommendation"
- **Indirectly (using an advisor):** "I would accept a robot's investment proposal if I could discuss the details with my financial advisor beforehand"

Using the two questions, we were able to identify those who completely rejected the use of a robot financial investment recommendation system, who were only open to it through human mediation, or, indeed, who would prefer such a robotic solution.

3 Data Collection

In our primary research, an online survey was used as our data collection methodology with targeted but convenience sampling (non-probability sampling). Convenience sampling is the prevailing non-probability approach where those respondents are selected who are at hand. This is commonly used in the case of websites, where visitors are exposed to invitations. Convenience sampling is frequently volunteer sampling, where the decision to participate depends on the respondents' willingness because the invitation is non-individualized [24]. With the data collection, we were mainly able to reach the readers of the Hungarian financial news portal, Portfolio.hu. Portfolio.hu is a financial and economic online news portal with micro- and macroeconomic news, analyses, and investor clubs & trader courses. Portfolio.hu was the 14th most visited Hungarian website, and the fifth news media site according to Similarweb statistics in July 2023 [25].

The preliminary assumption was that the readers of this predominantly economic online journal would be more aware of their financial decisions with higher financial and information literacy than average internet users. Research by Abreau & Mendes [25] on financial literacy and portfolio diversification concludes that investors' educational background and financial knowledge positively impact their investment diversification. We had to consider that it could have biased our research. However, choosing this target group is justified because the possible users of a future financial investment recommendation system in Hungary will also probably be members of this special target group.

Our data collection is carried out by an online questionnaire survey at the Portfolio.hu site from June 2019 until early September 2019 [27]. A promotional article for the questionnaire was published on 17 June 2019 and also appeared on the opening page of Portfolio.hu, where it remained available for a week [28].

The promotional article of the survey could also be read with a short warning text on Portfolio.hu's own Facebook page, and it could be found in one of the most visited Hungarian sites, index.hu portal in an allocated Portfolio.hu box, highlighting the materials specifically related to this financial news source. In addition, the article was available on other Hungarian news collection sites, such as Project Agora, Hírkereső, and Kapu.hu, and of course, it could be found in Google search. In addition, an invitation to the Portfolio.hu newsletter subscribers was also sent by e-mail, and not as a separate letter, but included in the standard newsletter with the article image (the number of subscribers was about 10,100 at the time of posting).

Based on Google Analytics data from Portfolio.hu, the article had just over four thousand pageviews and 3,536 unique pageviews, most of which were due to the index.hu box (1,021 views), which was followed by the Facebook page (408) and Project Agora (340). The average time spent on the page was 9 minutes and 45 seconds.

Readers from the various source pages first did not get to the questionnaire directly but to the article introducing the questionnaire, where they were able to read a short explanatory text before being invited to complete the questionnaire displaying the link. Seeing the introductory text before the survey allowed readers to be precisely aware of the nature and topic of the research even before learning about the questions, which helped them decide how relevant the topic of the questionnaire was to them. As far as we know during the data collection no special event occurred (e.g., news widely publicized) that could have influenced the research topic and could have biased the research results.

The research questionnaire ran on an engine developed by Portfolio.hu, which was able to "remember" the respondents so that the survey could be completed in more than one session, respondents could have a break and were capable to come back and complete the survey later. Participants could switch between pages while not losing their previous answers. Completion of the questionnaire was voluntary and anonymous, as no personal data was stored. The display of the questionnaire was responsive, meaning that respondents with different screen sizes could see the questionnaire in an optimized way for their device and were also able to answer questions on a touch screen. 27% of pageviews came from a mobile environment. The smaller screen size of mobile phones compared to computers affects the way questions are displayed and data entry may be also different. According to Toepoel & Lugtig [29: 157] “available studies often show mixed findings on for example response timings, break-off rates, and survey evaluation in mixed-device studies”. Hence it is important to design mobile-friendly online surveys to include respondents with different devices.

To complete the questionnaire, the system placed a cookie on the respondents’ computer, which checked the completion and the progress of the questionnaire. The questionnaire could only be filled in more than once if the respondent had intentionally deleted this cookie in advance and reloaded the page to complete again the questionnaire. We consider it as being unlikely that there would be multiple responses in the sample (since the participants had no interest in doing this), however, this cannot be completely ruled out. We did not use IP address filtering to prevent the multiple completion of the questionnaire, because a significant part of the Portfolio.hu readers browse the pages behind an institutional firewall and they appear under a common IP (e.g., banks), so a single response would have filtered out everybody else with the same IP and could make it impossible to respond to the survey.

The nearly four thousand pageviews resulted in a total of 1,539 questionnaire responses. According to Portfolio.hu’s measurements, it attracted over 200,000 visitors a day in 2019, so it can be said that the effect of self-selection bias [30] could be felt on two levels. On the one hand, only a very small proportion of the main page visitors clicked on the article (1.8%), and on the other hand, less than half of the clickers completed the questionnaire. As a result, less than 1% of Portfolio.hu readers completed the questionnaire and were included in our sample. Because of self-selection bias, the research is not representative for readers of the site. But that is entirely natural, and a normal part of the chosen sampling procedure. Thus, valid conclusions can only be drawn from the research for the respondents, and there is no opportunity for a broader generalization (e.g., for the readers of the Portfolio.hu or Hungarian internet users in general). The high affinity of the respondents for the topic is demonstrated by the fact that 47.5% of the sample had Invested in listed shares in the last three years, which can be considered rather atypical for the Hungarian adult population. Based on an OECD study [31], the number of active savers in Hungary was only 51.3% compared to the average OECD value of 70.4%. In 2016, CIB Bank and GfK investigated the savings habits of Hungarians [32]. According to the research, which was representative for 25-69 years old regular internet users, if the respondents had to invest five million forints:

- 35% would invest the money in real estate

- 30% would buy government securities
- 18% would buy precious metals
- 17% would keep it in a bank account
- 12% would choose investment funds [32]

In other words, only 12% would invest in funds that may include shares–-compared to the 47.5% in our sample, who invested real money in shares.

At the same time, the proportion of premium or private bank customers in our sample was 40%, which can also be considered extremely high. It is therefore highly probable that the questionnaire found a circle of respondents who are more open to investments than the average population, and who are familiar with the topic, rather than beginners or laypersons interested in the topic.

4 Research Results and Discussion

4.1 Missing Data

All questions except the age of the respondents were answered by more than 1,500 respondents, with the question regarding age being answered by only approximately half of the respondents.

About 40 respondents (less than 3% of the sample) did not answer most of the questionnaire (30-40 questions), and they were excluded from the analysis. Other respondents with partly incomplete questionnaires (with only a few unanswered questions) were included in the sample and analyzed despite the missing data. As the analysis was performed for groups of 4-6 variables (e.g., clustering on demographic data) the number of missing data was small (<2%) and over 95% of the samples were complete in each analytical step if the age variable was not involved in the analysis. Missing data can cause bias in the analysis and weaken the usability of the results [33][34]. Deleting non-complete cases results in the loss of information.

It is obvious that the proportion of missing data leverages the quality of statistical inferences. There is no agreement in the literature on the proportion of the acceptable percentage of missing data in a data set. Some authors offer the opinion that a missing rate of max 5% is inconsequential [35]. Other authors suggest that the analysis is seriously biased when the proportion is 10% or more [36]. As we know it is not only the proportion of the missing data that plays an important role in the quality of the statistical analysis, but also its randomness. In our study, the data were missing completely at random (MCAR), as no systematic bias was detected in the small amount of missing data, and therefore we are convinced that our analysis is insignificantly biased by the missing values. The analysis was performed in the R programming language with the standard missing data procedures where MCAR is applied.

4.2 Direct or Indirect Openness to Robot Recommendation

1,481 people of the total sample answered both questions related to the use of robot recommendation (direct and indirect use). We have re-coded the response options for both robot recommendation questions to ease of analysis as follows: 1 and 2 = 1 (rejecter), 3 = 2 (uncertain), 4, and 5 = 3 (adopter). On the direct question, 51% were rejecters, 32% were uncertain and only 17% – one in six respondents – were in favor of the solution. In comparison, there was already much more openness to using an indirect robot recommendation (with a human advisor): only 25% were rejecters, while 32% were still uncertain and 42% were adopters.

In addition to our socio-demographic and digital explanatory variables, we also analyzed the openness to robot recommendation in comparison with the risk-taking and economic saving variables, and we also looked at its relationship to banking status. Of these, only those are described below where we found a significant relationship, such as settlement type, age, digital subscription to online services, visibility settings in social media, and level of savings (the latter, however, only correlated with direct robot recommendation, but not when the relationship was indirect). However, there was no significant link to gender, education, job, usage of password management applications, level of risk-taking, and banking status, so we do not present these data.

4.3 The Link between Place of Residence and Robot Recommendation

In the case of the place of residence, the rejection level of direct use of the robot recommendation is below the average in the capital (48% compared to the average of 51%). While the level of rejection increases as the size of the settlement decreases, it already reaches 60% of respondents living in villages. The proportion of uncertain respondents ranges from 32% to 35% for all four types of settlements. In the case of the adopters, we can observe that its share is higher than the average in the capital, 21%, and its number decreases in direct proportion to the decrease in the size of the settlement, reaching the lowest value in villages (8%).

Based on these results it can be concluded that the degree of urbanization is directly proportional to the acceptance of the direct robot recommendation in our sample, the larger the settlement, the more willingness to accept the robot recommendation in the case of investment decisions.

In comparison, the relationship between the indirect use of the robot recommendation (using a human advisor as a mediator) and the type of settlement is not so clearly linear. Although Budapest (the capital of Hungary) is still the least dismissive (22%, compared to 27-30% in other settlements) and the level of uncertain respondents is almost the same (31%-36%), there is a significant increase of adopters in villages (8% to 39%) and in smaller towns (from 13% to 37%). In fact, the robot recommendation seems to be a fear of the unknown, and using human assistance greatly increases openness to the service. However, it is not necessary to provide this human assistance to everyone since some accept a robot's recommendation even without it.

4.4 The Link between Age and Robot Recommendation

There is also a significant link between age and openness to direct robot recommendation (see Table 1). However, in this case, there is no sign of a simple linear relationship, it is not true that the older someone in the sample is, the more rejective he would be. Although those over 65 are the most dismissive (71%), they are surprisingly followed by 15-19-year-olds (59%). 40-49-year-olds (52%) seem to be close to the average along with 20-29-year-olds (51%). Finally, 30-39-year-olds (45%) and 50-64-year-olds (44%) are less dismissive than the average.

Table 1
The link between openness to robot recommendation and age (N = 839 and N = 838). The first percentage shows the level of attitude towards the direct service, while the second shows the level of indirect service (with a personal advisor).

	1 – rejecter	**2 – uncertain**	**3 – adopter**
15-19	59% - 31%	28% - 34%	13% - 36%
20-29	51% - 24%	26% - 15%	23% - 61%
30-39	45% - 20%	37% - 42%	18% - 38%
40-49	52% - 27%	32% - 35%	16% - 38%
50-64	44% - 25%	39% - 31%	17% - 44%
65+	71% - 33%	26% - 38%	3% - 28%
Mean	*51%* - 25%	*32%* - 34%	*17%* - 41%

However, when accepting a direct service, we get a partly different picture, which is caused by the fact that the level of uncertain respondents is completely different in different age groups (it varies between 26% and 39%). Moving on to the range of adopters: 20-29-year-olds are the most accepting at 23%, followed by nearly 18%, 16%, and 17% acceptance levels of the three age groups between 39 and 64 years. The acceptance level of the robot recommendation is the lowest among those over 65, at only 3%, and 13% among those aged 15-19.

In comparison, the picture changes significantly when it comes to using a robot recommendation with a human advisor (see also Table 1, the second values in each cell). The rejection rate declines significantly, with the largest number among the oldest and 15-19-year-olds. Interestingly, the proportion of uncertain participants is completely different in separate age groups: it increases significantly over 65, and meanwhile only slightly increases in those aged 40-49, and decreases significantly in the age group 20-29 (from 26% to 15%). However, the proportion of adopters increased significantly in all age groups. Despite these results, it nevertheless cannot be stated that different age groups would respond in the same way to the advisory-supported use of the financial robot recommendation systems.

4.5 The Link between Subscription to Digital Services and Robot Recommendation

Openness to robot recommendation in financial investment is also significantly related to subscriptions to digital services. Those with such subscriptions are far less averse to direct robot recommendation (43% versus 56% of non-subscribers) and much more accepting (21% versus 14% of non-subscribers). On the other hand, it may be surprising, but the proportion of uncertain respondents is higher among subscribers (36% compared to 30% for non-subscribers).

In the case of an indirect robot recommendation, rejection decreases to 21% for subscribers (from 43% seen above) and 29% (from 56%) for non-subscribers. The proportion of uncertain participants was 32% in both groups – so it did not change. Finally, the acceptance rate rises to 47% for subscribers (from 21%) and 39% (from 14%) for non-subscribers.

It seems from the data as if digital subscribers would not be so dismissive, probably because they are better informed about the power of algorithms in music or streaming services (in finding new music or which movie/series to watch, for example). Yet they are still less able to decide whether robot recommendations would be suitable for them in financial investments as well.

4.6 The Link between Visibility Settings in Social Media and Robot Recommendation

The relationship between the changing visibility settings on social media sites and the openness to robot recommendations is also significant. Those who tend to change their settings are less reluctant (47% versus the 55% rejection level for non-visibility adjusters) and more accepting (19% versus the 15% acceptance level for non-visibility adjusters).

The situation is similar in the case of indirect robot recommendation, only the proportions are different because both groups are more open (46% of visibility adjusters on social media sites and 38% of non-adjusters are adopters). At the same time, visibility adjusters are much less dismissive (21% compared to 38% for non-adjusters). However, the proportion of the uncertain respondents remains above 30% here as well.

4.7 Relation between Level of Savings and Robot Recommendation

Finally, openness to direct robot recommendation is also related to the level of savings (see Table 2). Note, that the level of savings was only significant with the direct robot recommendation, so data from the advisor-assisted recommendation was not analyzed in this paper.

Table 2
Relationship between level of savings and robot recommendation (N = 1526)

What could you buy from your savings?	**1 – rejecter**	**2 – uncertain**	**3 – adopter**
property	56%	28%	15%
new car	49%	33%	18%
second-hand car	49%	36%	15%
holiday abroad	47%	32%	21%
smartphone	57%	37%	6%
have no savings	48%	28%	24%
Mean	*51%*	*32%*	*17%*

However, we cannot talk about a linear relationship here either. One of the most rejecting groups is composed of people with the most savings who could even buy a property (56% of them are rejecters compared to the average 51%). But the group with the least savings (who could only buy a smartphone with their savings) are, to a minor degree, even more dismissive, in their case, 57% are not open at all to direct robot recommendation. For the other savings groups, the rejection rate is slightly below average (ranging from 47% to 49%).

The level of uncertain respondents, in this case, is still relatively in a wide range (between 28% and 37%). While it may be surprising in the case of adopters, those with no savings at all are the most open (24%) and those with minimal savings (enough for only a smartphone) are the least open (6%). So, someone who already has some money set aside would be reluctant to entrust it to robots, while someone who does not have savings at all would be happy to take advice from robots (perhaps on how to save more efficiently). From this perspective, it seems worthwhile to gain the trust of those who do not have any savings right now and help them make a real difference as they begin to trust a robot's recommendation and stick to it if the service works for them.

4.8 Choosing an Algorithm of a Bank

As part of the research, we asked a question, which is remarkably similar to the robot recommendation, but less direct and more restrained. It requested that the respondents rank whose advice or what solutions they prefer when making their investment decisions:

- Bank algorithm
- Banking advisor
- Family
- Friends
- Choices of people like me (peers and people with similar careers, etc.)
- Social media recommendation
- I rely on myself

From the results, we constructed a variable that examines whether the respondent ranked the banking algorithm among the first three factors. 74 respondents in the total sample put the banking algorithm into the first place (about 5% of the sample) and another 687 people put it into the second or third place. A total of 761 people, 51% of the sample, did this.

However, the choice of the banking algorithm is unfortunately not significantly related to any of the explanatory variables of our research (gender, settlement type, education, job, age, password management, subscription of digital services, settings of visibility on social media sites, level of savings, risk-taking or banking status). Thus, it cannot be said that those who choose the banking algorithm would differ significantly in any way from those who rank the banking algorithm lower in making investment decisions, based on our examined aspects. This is good news in some ways, as it indicates that anyone can be open to such a service, and in some ways, it is bad news, because it indicates that it is not enough to ask someone just 2-3 well-targeted questions to know with certainty that they will be open to using a banking algorithm.

4.9 Clusters in Relation to Customer Openness to Robot Recommendation Systems

In addition to simple bivariate analysis, we also conducted a more in-depth analysis to find out what groups our respondents can be classified into in terms of accepting or rejecting a robot recommendation. As we have numerical and categorical variables, we used the Gower measure [37-39] that can be used to calculate the distance between two entities whose attributes have a mixture of categorical and numerical values. The optimal number of clusters was determined by the silhouette algorithm typically used for k-medoid or k-means clustering.

We used the “daisy” function from a package “cluster” to construct the matrix of the Gower distances in R. “Daisy” computes the pairwise distances (dissimilarities) between the sample elements. “Cluster” is an R package that contains methods for cluster analysis [40]. The variables may also be categorical. As we have mixed variable types in the questionnaire, the popular distance metrics such as Euclidean or cosine do not work, while daisy handles mixed variable types. Daisy computes all the pairwise distances between observations in the data set, the pam (partitioning around medoids) function for clustering and the “Rtsne” [41] package for constructing a low dimensional embedding of high-dimensional data for visualization.

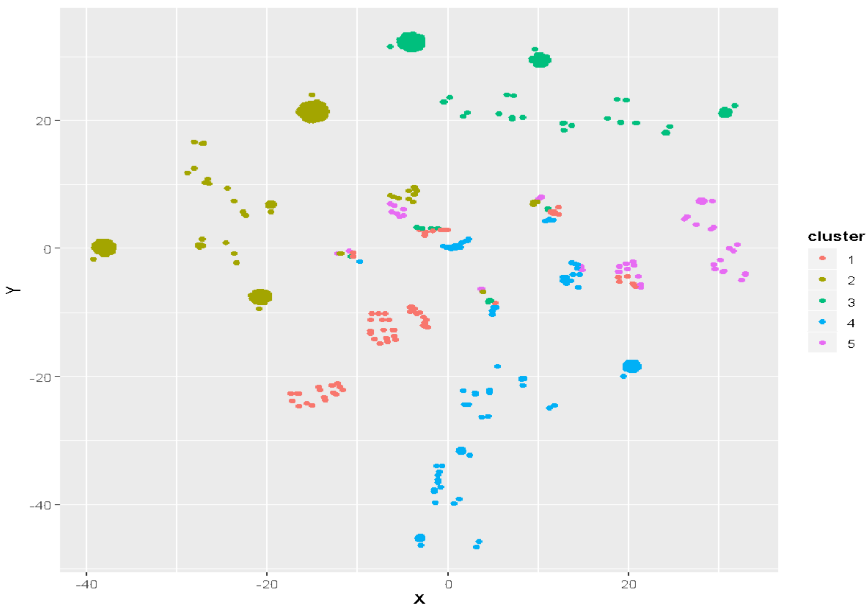

Figure 1

Relation to digital financial services, including robot advisors – optimal number of clusters: 5

The clusters were sufficiently balanced, and the difference in the number of cluster members was acceptable.

All non-clustered variables were used for profiling the clusters. In ”Relation to digital financial services, including robot advisors” cluster members No. 5 have the highest need for digital technology, they rated 3.6 on the 1-5-point scale with the option to change their banks if a better digital service were to be provided, while the next in line is cluster No. 3 with a rating of 3.15. Members of cluster No. 5 gave the second-highest average score of 2.81 on a 1-3-point scale to the acceptance of a robot advisor assuming they could discuss it with a human advisor. This cluster also provided the top rating of 4.57 (1-5 scale) for a digital platform that provides all information to the customer. Clearly, this cluster has the highest commitment to digital technology, including the robot advisors. Cluster No. 2 is the next in this row in the need for digital platforms while in cluster No. 2 the acceptance of robot advisors is the highest. Clusters No. 1, 3 and 4 also have an affinity for digital technology, but much less for robot advisors (2.19, 2.0 and 1.0 respectively).

The members of cluster No. 1 are the least interested in digital technology and they are in the middle if robot advisors are concerned. Members of cluster 4 have slightly less affinity for digitalization, than the others.

We analyzed the demographic data of the clusters to find specific demographic features. According to common belief and Rogers' theory on diffusion of innovations [1] younger people who live in cities and have a higher income are more susceptible to digital technology and services and thus more easily accept robot advisors. What we have found is that demographic data are not significantly different between the clusters.

The average age in the clusters varies between 36.8 and 40, a variation which is not significant. Their type of employment and the type of settlement they live in do not differ significantly either. The only slight difference is that members of clusters 5 and 1 are less well-off than the others.

Considering other, online features of the clusters, e.g., subscription to non-banking online services, cluster No. 4 is less susceptible to all digital services.

Conclusions

***Keep in mind what makes a robot recommendation system acceptable*:** One of the most important results of our research is what determines the direct or indirect (supported by a human advisor) acceptance of a robot recommendation system. Based on the results, roughly one in six respondents would be open on their own to a direct robot recommendation–- which is otherwise closely related to the respondent's degree of urbanization. However, many are uncertain, and many would only use the service with the support of human advisors, which would significantly increase the size of the target group that can be addressed.

***Let the robot teach us how to save better – a long-term relationship needs to be built*:** It is an interesting factor that even among those who do not have savings, there is an openness to the robot recommendation. If someone can learn how to save based on a robot's advice, they will be probably much more open to robot recommendations over time. All this shows that it is worth thinking about the long-term construction and design of the robot recommendation so that it can lay the foundations for a decade-long professional consulting relationship, in just the same way as good financial advisors can last a lifetime.

Youngsters must be educated as well: In the meantime, it is important to keep in mind – perhaps one of the most surprising and important results of our research–- that young people do not automatically accept a robot recommendation system either. 15-19-year-olds are often inexperienced in finance and, in many cases insecure, which cannot be counterbalanced at all by their experience in digital culture. So, education is especially important for youngsters, because even though they are digital natives that alone is not enough. On the other hand, what is extremely important is that they may still be customers for up to 50 years into the future.

Socio-demographic, digital culture and financial variables need to be mixed: During the analysis, different types of variables regularly showed a significant relationship with the examined questions: socio-demographic factors, digital variables, and financial variables. All this shows that it is not possible to build a successful robot recommendation system and an algorithm from only one of these three types of variables. Based on our results, it seems worthwhile to mix hard socio-demographic, digital cultural, and financial factors to create a better system.

The results need to be validated further in Hungary and international context: The research results can be used as input to create any savings and investment-related services. But in the meantime, it should be considered that our research was conducted in Hungary in a target group more open to savings and financial investment. It would be worthwhile to validate the research results in a representative online sample both in Hungary and at an international level.

***Broader potential implications from a DCR perspective*:** Our results highlight the correlations between cognitive reality perception and decisions believed to be rational, which many overlook. We suggest incorporating the DCR approach in designing future automated recommendation systems [21]. Digital transformation – such as the introduction of a robot recommendation system at an organization – must consider users' openness and cognitive abilities.

Furthermore, in the case of processes that previously required mainly human interaction (such as, for example, financial consulting), corporate management should consider building an ecosystem of traditional (in our case personal advisors) and pure digital technology solutions (robot recommendation). This combination results in hybrid human-digital systems, in which robots and humans cooperate and complex capabilities emerge. It seems to be a natural step in the recent history of human and information technology co-evolution.

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