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AKADÉMIAI KIADÓ

Understanding the societal and business perspectives of online trust literacy in the context of digitalization

ZSÓFIA CSERDI[1], PÉTER FEHÉR[2], MIRKÓ GÁTI[1]*, ÁRPÁD RAB[2] and KRISZTIÁN VARGA[2]

[1] Institute of Marketing, Corvinus University of Budapest, Budapest, Hungary

[2] Institute of Information Technology, Corvinus University of Budapest, Budapest, Hungary

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ABSTRACT

The spread of digital culture is one of the biggest reprogramming of humanity, radically transforming our economic, social, and cultural models. One of the keys to success of this transformation, and to preventing the spread of digital divides, is the development of a variety of literacies. These literacies describe the success of society and business to thrive in the digital space. In this article, we introduce a new concept of action literacy (online trust literacy) and examine its functioning from both a social and a business perspective through two primary research studies. After defining the phenomenon, we examine it from two sides: the first part examines the dimensional structure of trust from the perspective of society (through a large, representative sample-based survey), while the second part analyses the building and operational mechanisms of trust from a business perspective (through a small sample of exploratory data collection). The main implications of this study are to demonstrate the Janus-faced nature of this new kind of literacy and the ambiguity of digital culture to better understand the toolset of information recipients and providers. The result of our research is the introduction of a new concept of action literacy and its operationalisation, resulting in an interpretation matrix.

KEYWORDS

digital transformation, online trust, online trust literacy, recommender system, trust in technology

* Corresponding author. E-mail: mirko.gati@uni-corvinus.hu

1. INTRODUCTION

Culture is the survival strategy of humanity. As a species, we are doing well with the help of technological evolution, and in our five-thousand-year history, this is the most non-violent century in humanity. We have reached the Land of Abundance and look around a little uncertainly: the usual social, economic, regulatory, communication systems of recent centuries are being radically transformed because of our latest technological reprogramming: digital culture.

The primary function of digital culture in the history of mankind is that the humanity flowing into the cities, living densely there, forced into thousands of interactions and information every day, can cooperate with each other automatically and easily. It allowed friends and strangers, to work and collaborate with software and machines in an instant way, achieving their desired goals. The strength of humanity lies in cooperation. On the one hand, digital culture enables the efficient operation of strangers with each other, and on the other hand, it enables human-human, human-machine, and machine-machine interactions.

A very visible, widely used example of human-machine communication is a logic of recommender systems. Recommender systems are able to offer appropriate products and services to users based on customer preferences and needs, overcoming the limitations of human information retrieval and processing (Benabderrahmane et al. 2017). In recent years, recommender systems use artificial intelligence (AI) as their working principle and operate automatically on the basis of machine learning (Portugal et al. 2018). These algorithms perform information filtering based on the user's previous online search and purchase history, demographic data, GPS location, etc., with which they help the consumer decision-making process. They save customers time, as well as spare them the unnecessary effort that comes from human information retrieval (Park et al. 2012), and minimize risks (Bouneffouf et al. 2013). Most of the literature on recommender systems examines the accuracy of algorithms of different types of systems and their fit with consumer profiles from a technological point of view (Florea et al. 2017).

In our work, however, we approach the topic from a consumer perspective; since consumers' online trust literacy can be a serious barrier, which hampers both consumer usage benefits and their business returns. Therefore, the aim of our research is to map the working digital environment. In our view, this can only be approached in a holistic way, not the way it is traditionally done in the literature by looking at only one side. It is the interconnection of the two that creates value-creating interactions.

2. LITERATURE REVIEW

The concept of information literacy was born in the mid-seventies of the 20th century, indicating that – in addition to reading, writing and arithmetic – a fourth basic skill, namely the ability to navigate in an information environment, was ripe to be added to the others. The second generation of information literacy was about the skills needed to use digital resources effectively: searching, network navigation, administration, communication, displaying one's own content. By this time, almost all information activities had been consolidated on the network platform.

The world of third-generation literacies appeared as information operations were followed by an increasing number of elements of everyday social practice 'moving' into the virtual space, from shopping to job search to public activities. This phase, which the 'father' of information literacy calls 'action literacy' (Zurkowski 2014), is particularly important because it promises direct efficiency gains for individual and social actions (indirect efficiency gains and social progress can be expected from the support of information behaviour).

The successful development of third-generation literacy (Rab – Karvalics 2017) can promise to shorten the process of levelling out by developing, learning, and disseminating appropriate methodologies. This work can incorporate all the experiences of remedial solutions for the first two phases, community access, and domestic programmes supporting the use of the Internet by disadvantaged children, families, and communities.

Many of these actions can be identified as literacy, such as game literacy, scientific literacy, health literacy, participative literacy (Rab – Karvalics 2017). According to our research group, such action literacy is also online trust literacy. This literacy describes the ability to trust an online service or actor along certain characteristics, and how to build trust in a person or business service.

In our research, we were curious about how to create a common space of trust between consumers and service providers. How, according to what trust patterns, can consumers be grouped, and what business information can be used to address these groups to create a value-creating digital transaction. To this end, both sides were examined using primary data collection. From the consumer side, we looked at how the space of trust can be described and grouped, and from the service provider side, how these key target groups can be reached. Building trust can be approached in three ways: how we get information, how we judge its value to us, and how we maintain our trust space. Accordingly, our literature review addresses three areas: the concepts of information acquisition, privacy, and action literacy.

2.1. The psychological approach of information processing

Cognitive psychology worked the most with information processing (including information seeking and reception) among social sciences. Cognitive psychology studies the human being as an information processing system, describing the mental processes of perception, memory and information processing in order to understand the individual's processes of authoring information, making plans and solving problems. This cognitive process involves thinking, perception, memory, identification and problem-solving (Ingversen 1996). Information seeking is often seen as part of problem-solving thinking.

First and foremost, the problem needs to be of sufficient importance and perceived solvability. If the individual is sufficiently committed or motivated, then the search for information can begin. An individual must be able to collect, process, store and encode information. An individual's subjective initial beliefs and expectations, also known as initial knowledge, is the state of mind from which the search for information starts.

Stiegler's (1961) paradigm identifies four dimensions of information seeking: (1) what do we seek, (2) when do we seek it, (3) where do we seek it, (4) how do we seek it. The where and when questions are answered by identifying the sources of information that are often the focus of information-seeking research (Peterson – Merino 2003). The most important information sources are media (newspapers, television, radio, etc.), individuals (friends, salespeople, experts, etc.), sales (shops, catalogues), personal experience (product trial).

2.2. Online trust literacy

One of the first appearances of the term 'information literacy' dates back to 1974 and was closely related to the reform of education (especially in the United States) and concerned the effective use of information (Bawden 2001). Information literacy is practically the ability to use information effectively to solve a given problem. There is also an opinion that user education remains a library-centric education based on printed documents, while information literacy is a new paradigm that includes both computer and multimedia resources.

Information literacy appeared as a result of the development of information technology in the 1970s, it has expanded and strengthened over the last 30 years, and today it is the most important, respectively. It has become an unavoidable literacy of the 21st century (Bruce 2002), but the spread and deepening of digital culture requires the development of a new kind of literacy concept, therefore we created the concept of online trust literacy. Other conceptual models of literacy (see e.g. Ng 2012) exist with social-emotional, cognitive, and technical dimension, but in the present literature review, the trust dimension is thoroughly analysed.

The topic of trust is certainly present in the literature, with many authors feeling that one of the foundations of a functioning digital world is the availability of trust (Haider – Sundin 2020; Finkelstein 2019; Fisch – Seligman 2021). However, it is not defined as a focus and critical factor, but as a phenomenon available through other means. The need for trust literacy is most clearly expressed in Imazawa and Naoe (2010), who describe the field of education as one without which technology is powerless if mutual trust is missing. The secondary nature of technology is also highlighted by Li and Guo (2021). Overall, the issue of trust appears, but is not identified as a new capability, and we believe that it is this, and primarily not the specific technology, that should be focused on.

Online trust literacy is the ability to help us make the right decisions in trust games in the space of trust. The set of subtle perceptions that tell us how much we can trust a given information, service, digital identity.

Online Trust Literacy has five levels:

- formulation of the task to be performed;
- finding the actors of the relationship of trust to be built;
- building online trust;
- execution of the task;
- assess the task from a trust point of view.

The levels of online trust literacy build on each other in a logical progression. It is important to emphasise that the key is not the technology or access divide (although this is part of the problem), but the basis on which we trust someone or a service. An algorithm puts it in front of us based on our search history, or we compare recommendations, or trust in a platform elevates a service to the list of options, or a recommendation from a friend, for example, plays a role. On the social side, the interest is to find a service that does not abuse our trust and performs the task we have envisioned. On the business side, the aim is to make sure that the consumer chooses our service from a similar one and, in the best case, sees no alternative. On the one hand, online trust literacy aims at full information abundance and transparency, on the business side it aims at narrowing down the choices and at an information monopoly. It is this dichotomy that made it necessary to pair the two different data sets.

2.3. Privacy management

As already stated, customers may have privacy concerns with the recommender systems. This concept may be defined as individual's beliefs about the risks and potential negative consequences of information sharing (Cho et al. 2010). Privacy concerns greatly affect online user's privacy management decisions, which includes the use of social media, online information sharing behaviour, and participation in various privacy-protective activities, such as untagging photos, or deleting cookies (Baruh et al. 2017). By extension, privacy management can be an important part of personal information management (PIM). PIM is "both the practice and the study of activities people perform in order to acquire, organize, maintain and retrieve information for everyday use" (Jones 2007: 453), which presents users with increasingly complex tasks and challenges in the online space (Alon – Nachmias 2020).

However, research shows that individual's privacy concerns are not necessarily rationally reflected in their privacy management decisions (Chen 2018). This phenomenon is referred to 'privacy paradox' in the literature; while users in the online space are aware of the privacy risks they face, they are able to move beyond them, especially on social media, or by exploiting the benefits of e-commerce (Barth – De Jong 2017). In addition to achieving commercial value, there may be a need for personalized services in the sharing of personal data (Acquisti – Grossklags 2005). According to Kim et al. (2019), when providing privacy information for a better personalized service, people do not pay much attention to perceived privacy risk.

Online privacy literacy may also influence individual's privacy management behaviour (Baruh et al. 2017). According to Dienlin and Trepte (2015), users may not have experienced negative consequences of privacy abuse, resulting in an underestimation of privacy risks. In this consideration, it is important to highlight that privacy illiteracy reduces the chances of developing privacy concerns, and also hinders its reflection in individual's privacy management decisions (Baruh et al. 2017). Related to this, Park (2013) examined the role of digital literacy on privacy-related online behaviours, using three dimensions of digital literacy (familiarity with technical aspects of the Internet; awareness of common institutional practices; and understanding of current privacy policy). Apart from these factors, we argue that self-education in privacy literacy can lead to better privacy management decisions. In order to increase user confidence and avoid data misuse, the recent literature on recommender systems emphasizes the methods by which privacy protection can be implemented, without sacrificing the degree of recommendations' accuracy, possibly demonstrating even higher performance (Mazeh – Shmueli 2020; Meng et al. 2019).

3. RESEARCH METHODOLOGY AND SAMPLING

The approaches so far have examined the characteristics of the consumer and service provider side separately. In our new approach, these need to be examined in a unified, single system. To this end, we also analyse social and consumer data, as well as data collected for business purposes. One of the major novelties of our research is the theoretical framework in which we have combined the two (see Table 1).

Table 1. Conceptual layers

Layer 1: Information processing					
Information sources (M2)	Trust towards information sources (M3)		Information sources (alone or with the help of others) (Q12)	Decision related to financial decisions (spontaneous or planned) (Q11)	Planning (vacation) (Q10)
Layer 2: Online Trust Literacy					
Trust in AI systems (M17)	Concerns related to internet use (I4)	Digitalization attitude (M7)	Trust in digital technologies (Q1-Q4)	Trust in AI systems (Q6)	
Layer 3: Privacy management					
Privacy attitude (M14)	Trust towards personal data storage location (M15)	Training (M9, M10)	Privacy attitude (Q5)	Online buying behaviour (Q17)	Training (Q18, Q20)

Source: authors.

3.1. Databases

The social part was performed with the help of the international research databases of the National Civil Service University in Budapest, Hungary. The aim of the research was to map internet use habits, online trust and fear of manipulation. With the help of large-sample, representative databases, we were able to measure the attitudes of the target consumer group. The data collection was carried out in a representative way in four countries of the Central European region (the Visegrád Group: Czech Republic, Hungary, Poland and Slovakia). Data collection was performed using the CATI methodology in the fall of 2019. Our calculations were performed on the Hungarian subsample. Thus, our sample consists of $N = 1{,}003$ people, of which 52.8% are women and 47.2% are men. The average age of the respondents is $M_{age} = 49.2$ years, the age range is 18–89 years with a standard deviation of 16.8 years. Among the age categories, in order to distinguish two important target groups of the market and also to present comparable results with our other sample, we focus on the groups between 25 and 34 (13.4%) and 35–44 (17.8%). Based on the distribution of the sample by place of residence, 17% live in the capital city (Budapest), 20.8% in county seats, 32.9% in other cities, and 29.2% in villages.

The business perspective part was performed with the help of a research and development (R&D) project dataset, focusing on developing digital solutions for investment activities. Data were collected through structured interviews, collecting both qualitative and quantitative data. The project aimed to create digital solutions for investment activities, more than 60 international students were working with us during the data collection and in the whole project. The target group of the survey was the whole population who can articulate any need or problem in investment. In this research, quantitative data were analysed. Data was collected in 2019 Q4 and 2020 Q1, and the sample consists of 1,095 respondents. The database has respondents mainly

from Hungary (73.3%), Central and Eastern Europe (CEE, 18.4%), and from the rest of Europe (8%). In these data collection, age categories of 25–34 (38.2%) and 35–44 (31.7%) are over-represented, but these categories present the main focus of our research. Regarding the educational background, the sample is overrepresented by college/university degree holders, and most of the respondents are employed full-time (74.2%). During the analysis – as written before – we concentrate on the 25–34 and 35–44 age categories.

3.2. Linking the two research studies into a consumer- and service provider-oriented framework

In order to take a holistic approach, we have developed the characteristics of the consumer and service provider side in a unified framework. We have identified three levels that point to the depth and richness of value-creating operations. It should be emphasized that these value-creating operations can not only be material, but also have a role to play in social dialogue, education or e-government.

Table 1 describes our summary framework based on the databases at the question and variable level. These points will be analysed in detail later.

Building the matrix is based on three steps: getting the information, trusting the information, and finally, maintaining that trust. The levels of the matrix in Table 1 have been presented in our literature review, and some of its elements are a systematisation of the relevant questions from the two surveys. The construction of the framework necessarily involved trade-offs, since we were setting up two specific databases. Further research on this topic can be based on the results of this research to build a more controlled, symmetric data set.

At the first level, from a social perspective, we examined what sources of information are used and how much respondents trust them. Frome the business perspective, we also examined the sources of information, but also how consciously we can use them.

At the second level, in addition to trust attitudes about online space, we examined trust in the Internet and trust in content provided by machines. This is the receiving medium into which business information arrives. From a business perspective, we looked at how much they trust digital technologies and smart systems.

At the third level, we examined the level of action that can be measured through data provision and use. From a business perspective, we measured shopping habits, awareness of action in online space, as opposed to social data in the areas of personal data management and self-education.

Altogether, the different nature of databases and sample characteristics, together with the measurement levels of the operationalized variables, our exploratory study does not necessarily require multivariate statistics to analyse. Furthermore, the focus was to find statistics that can be applied on both databases, to be able to make a valid comparison (in this case, univariate statistics were applicable to accomplish this task).

4. RESULTS

4.1. Study 1: Societal perspective

Layer 1: Information processing. In Study 1, in connection with the first level of our theoretical model, we analysed how, on what surfaces the respondents collect information and how much

they trust their authenticity. The research distinguished eight different channels, moving from personal sources of information (reports of friends and acquaintances) through traditional mass media (television, radio, printed national dailies, printed local dailies) to the online space (social media, internet news sites/mobile applications, online news aggregation solutions).

Regarding the frequency distribution of the sources of information acquisition, we also analysed our results in the whole sample, and then as the difference between the two key age categories. Based on the analysis of Pearson's Chi-Square Test, we obtained the following results in the logical order of the sources. The connection between the frequency of friends and acquaintances as a source of information collection and age categories was found to be significant in the whole sample (sig = 0.001, $a = 16.7\%$, the test is reliable). In terms of the strength of the relationship, it is weak (Cramer's V = 0.109). However, if we examine only the two categories (25–34 and 35–44, respectively), the difference between the categories disappears, in this case there is no correlation between the age category and the frequency of obtaining information from friends (sig = 0.130, $a = 16.7\%$, test is reliable).

In the case of traditional mass media, we obtained similar results for television; in the whole sample there is a difference in the frequency of television information acquisition between age groups (sig = 0.000, $a = 16.7\%$, the test is reliable), the strength of the relationship is weak (Cramer's V = 0.181). If we examine the two groups prominently, however, there is no difference in the frequency of television-based information collection (sig = 0.9444). Similarly, in the whole sample there is significant relationship between frequency of radio-based information acquisition and age categories, but in the case of the two highlighted age groups, no significant relationship can be detected. In the whole sample, the strength of the relationship (sig = 0.001, $a = 16.7\%$, the test is reliable) is weak (Cramer's V = 0.125), however, the Pearson's Chi-Square Test no longer yielded significant results for the two age groups (sig = 0.090). However, in the case of printed national dailies, a significant relationship can be observed in the total sample and between the two age groups. Examining the whole sample, the strength of the relationship (sig = 0.000, $a = 16.7\%$, the test is reliable) is weak (Cramer's V = 0.127). In case of selecting the two age groups, the strength of the relationship (sig = 0.031, $a = 16.7$) is weak but higher than it was measured in the whole sample (Cramer's V = 0.198). Moving on to printed local dailies, the trend returns to the pattern of the first two mass media types; a significant relationship was observed in the whole sample (sig = 0.000, $a = 16.7\%$, the test is reliable), the strength of the relationship was weak (Cramer's V = 0.114). Based on the individual examination of the two age groups, no significant relationship can be observed between the frequency of information acquisition from printed local papers and age groups based on the Pearson's Chi-Square Test (sig = 0.200, $a = 16.7\%$).

The examination of digital platforms revealed that significant relationship cannot be found between the frequency of information collection and age categories, neither in the whole sample, nor by focusing on the highlighted age groups. Based on the entire sample for social media, the significance level for Pearson's Chi-Square Test: sig = 0.170, for online news sites/mobile applications: sig = 0.251, for online news aggregation solutions: sig = 0.504 ($a = 16.7\%$ in all cases).

We also examined respondents' trust levels towards the same information sources. The most reliable source for the whole sample is friends and acquaintances ($M = 3.53$ SD = 0.954). The average confidence level of the 25–34 age group is slightly below the group average ($M = 3.51$), while the 35–44 age group shows higher confidence in the authenticity of information from

friends and acquaintances ($M = 3.59$). However, the difference is not significant based on analysis of variance; in the calculated ANOVA table the significance level for the *F*-test is sig = 0.900, i.e. the means do not differ significantly (prerequisite: significance level for Levene's test: sig = 0.877, the result of the *F*-test for variance can be performed with sufficient reliability).

Moving to traditional media, radio proved to be the second most reliable source of information in the whole sample ($M = 3.3$ SD = 1.037). In case of television and radio there is a negligible difference between the averages of the two age groups, however, both highlighted age groups trust printed local dailies compared more than the average of the whole sample ($M = 3.14$, $M_{25\text{-}34} = 3.17$, $M_{35\text{-}44} = 3.21$). Based on the analysis of variance (examining given surfaces individually), the means of the groups do not differ significantly from each other in relation to trust towards traditional media platforms. Successful Levene's tests showed that the analysis of variance can be performed reliably in each type of mass media sources ($sig_{TV} = 0.357$; $sig_{radio}0.861$; $sig_{nat.newsp.} = 0.274$; $sig_{localnewsp} = 0.651$). However, the significance levels for the *F*-test in the ANOVA tables exceeded the target level of confidence (5%) in all cases, so there is no significant relationship between the degree of trust towards mass media types and the age groups ($sig_{TV} = 0.982$; $sig_{radio} = 0.843$; $sig_{nat.newsp} = 0.662$; $sig_{localnewsp.} = 0.873$).

Out of overall eight surfaces, the lowest average was given to social media ($M = 2.78$ SD = 0.938), which was equally more negatively assessed by the two priority categories ($M_{25\text{-}34} = M_{35\text{-}44} = 2.75$). In the case of social media interfaces, the significance level for the Levene's test: sig = 0.024, Internet news sites/mobile applications: sig = 0.093, news aggregation solutions: sig = 0.070. Thus, the result of the *F*-test for the analysis of variance cannot be performed on online sources with sufficient reliability.

Layer 2: Online trust literacy. In Study 1, online trust literacy displayed on the second level of our model relies on three factors; we first examine respondents' trust in artificial intelligence systems. Then the extent of concern about Internet use and their attitude toward digitalization will be analysed. Similarly, we interpret these topics in the whole sample, and the two selected age groups will be highlighted.

Respondents' trust in artificial intelligence is analysed in four different areas of activity located at different levels of responsibility. Areas of activity include public administration, medical diagnosis, business/financial consulting, and employment consulting. In the total sample, more than half of the respondents (52.4%) would trust AI-based public administration systems only if supplemented by human service (complete distrust in AI: 28.5%, trust in AI: 13.9%). The proportions of the two priority age groups in each category are virtually identical; the proportion of distrust is lower than the proportion of the total sample, which is 28.2% (25–34: 24.6%; 35–44: 25.1%). In the human assisted version, trust was included in a higher proportion compared to the sample (25–34: 58.2%; 35–44: 58.1%). The proportion of those who fully trust in AI-based public administration was slightly higher than the proportion of the total sample (25–34: 14.2%; 35–44: 14%). Based on the significance level for the Pearson's Chi Square Test calculated for the whole sample (sig = 0.007), the difference in the age groups is significant ($a = 0$, test result is reliable), the relationship is weak (Cramer's V = 0.095). However, there was no statistically significant difference between the two priority categories (sig = 0.999; $a = 12.5\%$).

Examining trust in an artificial intelligence-based medical diagnosis, the human assisted AI solution is preferred in a similar proportion (54.3%) as in public administration, but the

proportion of those who fully trust in AI-based medical diagnosis has fallen below 10% due to increased responsibility (9%). Regarding the two age categories, in contrast to the same proportions of the previous AI-system, minor differences can be observed. In both categories, trust in human-assisted AI solutions is higher than in the sample (25–34: 58.2%; 35–44: 62.6%), while the proportion of those who fully trust in AI is lower in both groups (25–34: 5.2%; 35–44: 5.6%). Based on the significance level for the Pearson's Chi Square Test (sig = 0.000), there is a significant, weak relationship (Cramer's V = 0.118) in the overall sample between age group and trust in medical diagnosis supported by artificial intelligence ($a = 4\%$, test result reliable). Examining the two highlighted categories, there is no significant relationship (sig = 0.838), however, the test result is unreliable as more than 20% of the cells contain less than five respondents ($a = 25\%$).

Analysing trust in artificial intelligence system-based business/financial consulting in the whole sample, only half of the respondents prefer the solution supplemented with human factor (50.5%) as in the previous cases, but the proportion of clients who fully trust in the AI-system decreased further (8.5%). In the two priority age groups, the proportions converged similarly; but overall differently from the proportions of the total sample. The proportion of totally distrustful respondents was lower than the proportion of the sample (25–34: 29.1%; 35–44: 26.3%), and the human-supported AI version was voted higher in both groups (25–34: 57.5%; 35–44: 61.5%). The proportion of AI-supporters was slightly higher than the proportion of the whole sample (25–34: 10.4%; 35–44: 9.5%). Based on the significance level (sig = 0.000) for the Pearson's Chi Square Test calculated for the whole sample, the difference in the age groups is significant ($a = 0$, the test is reliable), the relationship is weak (Cramer's V = 0.131). In the case of the two priority categories, there is no statistically significant difference in trust in artificial intelligence based business and financial consulting systems (sig = 0.917; $a = 12.5\%$).

Examining trust in case of artificial intelligence-based labour counselling, in the whole sample proportions are similar to those of public administration. The proportion of those who prefer AI-assisted labour counselling performed exclusively with human support is 54.1%, the proportion of those who are completely distrustful in AI is 26.6%, and the proportion of those who trust in AI is 12.5%. The 25–34 age group trusts more in artificial intelligence when it comes to job counselling; in their case, the proportion of distrusts is 18.7%, the human assisted AI version is 64.2%. In case of the two age groups, compared to the whole sample, the proportions of those who trust AI-based labour counselling only if supplemented with human factor (25–34: 64.2%; 35–44: 56.4%) and those who fully trust AI are also higher (25–34: 14.2%; 35–44: 17.3%). Based on the significance level for the Pearson's Chi Square Test (sig = 0.000), there is a significant, weak relationship (Cramer's V = 0.140) in the overall sample between age group and trust in AI-assisted employment counselling ($a = 0\%$, test result reliable). Examining the two highlighted categories, there is no significant relationship (sig = 0.488), however, the test result is unreliable as more than 20% of the cells contain less than five respondents ($a = 25\%$).

Concerns about Internet use were measured by the questionnaire in terms of the frequency with which respondents abstained from using the Internet because they would leave traces in the digital world. Examining the entire sample, 62.8% of the respondents did not mention this at all, 26.5% had already done so, but only rarely, and in 10.3% of the cases this occurred frequently. A similar distribution is observed in the 25–34 age group; it was not mentioned at all by 59.5% of the age group, in 29.3% it was rare, and in 10.3% it was common to abstain from using the Internet. The proportions are similar within the 35–44 age group category; in 60.3% it was not

mentioned, 28.8% have already experienced it but rarely, 10.3% abstained often from the Internet. Based on the significance level for the Pearson's Chi Square Test (sig = 0.479), there is no difference between the age groups in the frequency of anxiety related to Internet use, however, it is important to highlight that more than 20% of cells contain less than five respondents ($a = 25\%$), therefore, the test result is not reliable.

Analysing the attitude towards digitalization, in the whole sample the vast majority of respondents (66.5%) value the rapid development of online activities as an opportunity for the individual and society. Half of the sample (51.2%) evaluates it rather as an opportunity, the remaining part (15.3%) consider it exclusively as an opportunity. Only 4.1% evaluate it as an explicit risk, with more than half of the responses coming from those over 55 years of age. Comparing the proportions of the two priority groups to the distribution of the total sample, in both age groups fewer people think of digital services and activities as an expressed risk (25–34: 2.2%; 35–44: 2.8%). In the 25–34 age group more people consider digital services and activities rather as a risk compared to the total sample, while the 35–44 age group is less sceptical (21.8%). The continuity of the trend is also reflected in the evaluation of digitalization exclusively as an opportunity; the 35–44 age group presents a higher proportion compared to the distribution of the whole sample (18.4% within the category). Although minor differences can be observed between age groups, overall, based on the significance level (sig = 0.148) for the Pearson's Chi Square Test, there is no significant relationship between age categories and attitudes towards digitalization. Less than 20% of the cells contain less than five respondents ($a = 4\%$), the test result is reliable.

Layer 3: Privacy management. In the third layer of our model, privacy management factors were analysed, using three topics in Study 1. First, the willingness of respondents to provide personal data was examined. As a second factor, respondents' level of trust towards personal data storage location was captured. Finally, we investigated whether and how they train themselves against the challenges of the online world.

In the case of their willingness to provide personal information, we analysed what specific personal data would respondents be willing to provide if they were offered a very attractive, free service. Among the predefined personal data types, the most sensitive ones in order are the following: bank card number ($n = 14$), bank account number ($n = 18$), social security number ($n = 87$), licence plate number ($n = 116$). Less sensitive categories included address ($n = 200$), health information ($n = 257$), travel information ($n = 274$), and age ($n = 780$). The order of sensitivity is the same for both the two highlighted age categories and the entire sample. Furthermore, in general, it can be observed that those in the younger category showed a greater willingness to provide their personal data, while the difference was not significant.

Respondents' trust level towards different personal data storage locations was also examined. The following list can be compiled in order of reliability level in the sample: doctor's office ($M = 3.44$, SD = 0.801), account holding bank ($M = 3.37$, SD = 0.858), local government ($M = 3.26$, SD = 0.821), state institutions ($M = 3.03$, SD = 0.990), telecommunication service provider ($M = 2.87$, SD = 0.955), own computer ($M = 2.55$, SD = 1.002), car services ($M = 2.45$, SD = 0.979), own smartphone operating system ($M = 2.44$, SD = 0.993), online services ($M = 2.13$, SD = 0.922), Google ($M = 1.89$, SD = 0.902), Facebook ($M = 1.72$, SD = 0.846) and online advertising portals as least secure interfaces ($M = 1.69$, SD = 0.797.). For the two age categories, the older age group (35–44) is slightly more distrustful of the data management

security of online sources. Furthermore, they feel more secure about their data in the case of trust-based services compared to the younger generation, however, the differences did not prove to be significant. Significant differences among reliability averages were found in case of four sources (own computer, own smartphone, online services, and Facebook) in the whole sample, based on the evaluation of age group.

Speaking of training against the challenges of the online world, 71.4% of respondents do not prepare in any way. The proportions of the two highlighted age categories are almost the same as the proportions of the total sample. In the case of the 35–44 category, the proportion of self-educators is minimally higher (30.2%) compared to the 25–35 age group (28.4%). Although there was no significant relationship between age categories and training according to the significance level for the Pearson's Chi Square Test (sig = 0.597), the test result is unreliable because more than 20% of the cells contain less than 5 respondents ($a = 33.3\%$). Based on the training sources of the respondents who trained themselves in the whole sample (more than one answer were allowed to choose), the help and information of friends and acquaintances was the most popular (151 mentions), followed by reading professional materials and articles (135 mentions), followed by help from colleagues (85 mentions). However, the younger age group, 25–34, most frequently mentioned the reading of professional materials and articles as a source of training, followed by the help and information of friends and acquaintances, and then that of colleagues. In the 35–44 age group, the order was the help of friends, professional materials, reading articles and information of colleagues. For the two age groups, the help of specified courses and the help of experts was similarly negligible.

The summarized results of the societal perspective can be found in Table 2.

4.2. Study 2: Business perspective

Layer 1: Information processing. Study 2 analysed how respondents gather information (e.g., they decide alone, or with the help of others; they make decisions spontaneously or in a more planned way; they plan their holidays or go on vacation without conscious scheduling). Results are analysed for the whole sample, and for the highlighted two age groups.

Considering the question how far the respondents plan their holidays ahead, it seems that altogether most respondents plan their holidays more than 8 weeks ahead (35.8%), and 24.5% plan 6–8 weeks before the actual vacation. In the two highlighted age groups (25–34, 35–44), it seems that although the younger age group has higher values in the longer planning periods, there is no significant difference (sig = 0.898). If the whole sample is analysed from this perspective, it can be seen that there is a significant difference in the way how respondents plan their holiday (sig = 0.037). Considering the strength of the relationship, the Cramer's V shows a weak relationship (Cramer's V = 0.105).

The next variable under the topic of information seeking was the decision related to financial tasks, where the ad-hoc or planned nature of financial decision-making was analysed. Based on the results, the majority of respondents plan their holidays based on a significant amount of information (65.7%). Considering the two highlighted age groups (25–34, 35–44), there is no significant difference (sig = 0.699) whether younger or older respondents make decisions about their holidays. Looking at the whole sample it can be concluded that there was no significant difference among the age groups in the sample.

Table 2. Study 1 results – Societal perspective

Layer 1: Information processing				
Information sources (M2)	***Analysis used: Pearson's Chi-Square Test, Cramer's V***			
friends and acquaintances	full sample.: significant, weak relationship			between the two age categories: not significant
television	full sample.: significant, weak relationship			between the two age categories: not significant
radio	full sample.: significant, weak relationship			between the two age categories: not significant
printed national dailies	full sample.: significant, weak relationship			between the two age categories: significant, weak relationship
printed local dailies	full sample.: significant, weak relationship			between the two age categories: not significant
social media	full sample.: not significant			between the two age categories: not significant
internet news sites/mobile applications	full sample.: not significant			between the two age categories: not significant
online news aggregation solutions	full sample.: not significant			between the two age categories: not significant
Trust towards information sources (M3)	***Analysis used: means, ANOVA (F test, Levene's test)***			
friends and acquaintances	$M = 3.53$	$M_{25\text{-}34} = 3.51$	$M_{35\text{-}44} = 3.59$	ANOVA between the two age categories no significant difference
television	$M = 3.13$	$M_{25\text{-}34} = 3.14$	$M_{35\text{-}44} = 3.14$	ANOVA between the two age categories no significant difference
Radio	$M = 3.3$	$M_{25\text{-}34} = 3.32$	$M_{35\text{-}44} = 3.28$	ANOVA between the two age categories no significant difference
printed national dailies	$M = 3.14$	$M_{25\text{-}34} = 3.17$	$M_{35\text{-}44} = 3.02$	ANOVA between the two age categories no significant difference
printed local dailies	$M = 3.14$	$M_{25\text{-}34} = 3.17$	$M_{35\text{-}44} = 3.21$	ANOVA between the two age categories no significant difference

(continued)

Table 2. Continued

social media	$M = 2.78$	$M_{25\text{-}34} = 2.75$	$M_{35\text{-}44} = 2.75$	homogeneity of variance not fulfilled
internet news sites/mobile applications	$M = 3.1$	$M_{25\text{-}34} = 3.13$	$M_{35\text{-}44} = 3.17$	homogeneity of variance not fulfilled
online news aggregation solutions	$M = 3.11$	$M_{25\text{-}34} = 3.07$	$M_{35\text{-}44} = 3.22$	homogeneity of variance not fulfilled
Layer 2: Online trust literacy				
Trust in AI systems (M17)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V***			
public administration	full sample.: significant, weak relationship		between the two age categories: not significant	
medical diagnosis	full sample.: significant, weak relationship		between the two age categories: not reliable (a value)	
business/financial consulting	full sample.: significant, weak relationship		between the two age categories: not significant	
employment consulting	full sample.: significant, weak relationship		between the two age categories: not reliable (a value)	
Concerns related to internet use (I4)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V***			
never occur	full sample: 62.8%	25–34: 59.5%	35–44: 60.3%	relationship in full sample: not significant, but not reliable (a value)
rarely occur	full sample: 26.5%	25–34: 29.3%	35–44: 28.8%	
frequently occur	full sample: 10.3%	25–34: 10.3%	35–44: 10.3%	
Digitalization attitude (M7)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V***			
opportunity for ind. and society	full sample: 15.3%	25–34: 14.2%	35–44: 18.4%	relationship in full sample: not significant, reliable (a value)
rather opportunity for ind. and society	full sample: 51.2%	25–34: 53.7%	35–44: 51.4%	

(continued)

Table 2. Continued

rather risk for ind. and society	full sample: 23.3%		25–34: 24.6%	35–44: 21.8%	
explicit risk for ind. and society	full sample: 4.1%		25–34: 2.2%	35–44: 2.8%	
Layer 3: Privacy management					
Privacy attitude (M14)	***Analysis used: Frequencies***				
Most sensitive personal data types	Bank card nr.: $n = 14$		Bank account nr.: $n = 18$	Social security nr.: $n = 87$	Licence plate nr.: $n = 116$
Least sensitive personal data types	Address: $n = 200$		Health inf.: $n = 257$	Travel inf.: $n = 274$	Age: $n = 780$
Trust towards personal data storage location (M15)	***Analysis used: means, ANOVA (F test, Levene's test)***				
Doctor's office	$M = 3.44$	SD = 0.801	$M_{25\text{-}34} = 3.44$	$M_{35\text{-}44} = 3.48$	homogeneity of variance not fulfilled
Account holding bank	$M = 3.37$	SD = 0.858	$M_{25\text{-}34} = 3.48$	$M_{35\text{-}44} = 3.44$	homogeneity of variance not fulfilled
Local government	$M = 3.26$	SD = 0.821	$M_{25\text{-}34} = 3.3$	$M_{35\text{-}44} = 3.27$	ANOVA all age categories: no significant difference
State institutions	$M = 3.03$	SD = 0.990	$M_{25\text{-}34} = 2.99$	$M_{35\text{-}44} = 3.1$	ANOVA all age categories: no significant difference
Telecommunication service provider	$M = 2.87$	SD = 0.955	$M_{25\text{-}34} = 2.88$	$M_{35\text{-}44} = 3.02$	homogeneity of variance not fulfilled
Own computer	$M = 2.55$	SD = 1.002	$M_{25\text{-}34} = 2.74$	$M_{35\text{-}44} = 2.66$	ANOVA all age categories: significant difference
Car service	$M = 2.45$	SD = 0.979	$M_{25\text{-}34} = 2.5$	$M_{35\text{-}44} = 2.5$	homogeneity of variance not fulfilled
Own smartphone operating system	$M = 2.44$	SD = 0.993	$M_{25\text{-}34} = 2.69$	$M_{35\text{-}44} = 2.54$	ANOVA all age categories: significant difference

(continued)

Table 2. Continued

Online services	$M = 2.13$	SD = 0.922	$M_{25\text{-}34} = 2.33$	$M_{35\text{-}44} = 2.2$	ANOVA all age categories: significant difference
Google	$M = 1.89$	SD = 0.902	$M_{25\text{-}34} = 2.11$	$M_{35\text{-}44} = 1.84$	homogeneity of variance not fulfilled
Facebook	$M = 1.72$	SD = 0.846	$M_{25\text{-}34} = 1.86$	$M_{35\text{-}44} = 1.71$	ANOVA all age categories: significant difference
Online advrtising portals	$M = 1.69$	SD = 0.797	$M_{25\text{-}34} = 1.76$	$M_{35\text{-}44} = 1.76$	homogeneity of variance not fulfilled
Training (M9, M10)	***Analysis used: Crosstabulation, Frequencies, Pearson's Chi-Square Test, Cramer's V***				
Positive training attitude	full sample: 29.5%		25–34: 28.4%	35–44: 30.2%	full sample: not significant, but not reliable (a value)
Source: friends and acquaintances	$n = 151$			$n_{25\text{-}34} = 19$	$n_{35\text{-}44} = 31$
Source: professional materials, articles	$n = 135$			$n_{25\text{-}34} = 24$	$n_{35\text{-}44} = 30$
Source: help from colleagues	$n = 85$			$n_{25\text{-}34} = 13$	$n_{35\text{-}44} = 21$
Source: specified courses	$n = 59$			$n_{25\text{-}34} = 11$	$n_{35\text{-}44} = 10$
Source: help of experts	$n = 43$			$n_{25\text{-}34} = 9$	$n_{35\text{-}44} = 8$
Source: other	$n = 17$			$n_{25\text{-}34} = 2$	$n_{35\text{-}44} = 2$

Source: authors.

Gathering information can be made alone, or with the help of others. Someone can decide to ask others for a better outcome, especially in money-related decisions. Although the respondents seem to decide rather alone in the case of the older age group (35–44), while the younger age group (25–34) tends to decide with the help of others, there is no significant difference (sig = 0.206) between these age groups. If the whole sample is analysed, there is no difference among the age groups in the sample either.

Layer 2: Online trust literacy. Study 2 aimed to analyse online trust literacy, namely how respondents trust digital technologies in general, and especially artificial intelligence (AI) systems. Results are analysed for the highlighted two age groups, and for the whole sample, and these analyses show respondents' trust towards digital systems.

In the case of digital trust, respondents have relatively higher values in the younger age group (25–34) and lower in the older one (35–44), but the difference is not significant between the two groups (sig = 0.382). At first sight, older age groups show the lowest trust towards digital systems and younger age group the highest, however the difference is not significant. The results show interesting differences in the whole sample. The significance level to the Levene's test is 0.019, so homogeneity of variance persists, and the *F* test of variance analysis can be conducted with enough reliability. Based on the *F* test results, the significance level is 0.000 in the ANOVA table, so trust in digital technologies differs in the whole sample significantly, having a decreasing value as age increases.

AI systems seem to be rather useful in the opinion of the respondents, 85.9% believe that these systems are somewhat useful to humanity. When we look at the difference between the two age groups, no significant difference is visible (because the majority of the respondents believe that these systems are rather useful). When the whole sample is analysed, the following relationships can be shown: the significance level of the Levene's test is 0.002, so homogeneity of variance persists, and the *F* test of variance analysis can be conducted ensuring reliability. Based on the *F* test results, the significance level is 0.000 in the ANOVA table, so trust in AI systems differs in the whole sample significantly, showing a decreasing value as age increases, similarly to the case of digital technologies.

Layer 3: Privacy management. In Study 2, the third layer of the conceptual framework is online privacy management and behaviour, where respondents' proclivity was measured how sensitive and less sensitive data would they provide if they were offered a free service. Furthermore, respondents' online buying behaviour was explored in terms of the products they would buy online. Finally, their their free time and time for self-development was measured.

The most sensitive data reported by the respondents are the following: social security number ($n = 57$), bank account number ($n = 66$), bank card number ($n = 71$), licence plate number ($n = 117$). The less sensitive data that respondents tend to give if they were offered a free service are the following: health information ($n = 134$), travel information ($n = 300$), address ($n = 322$), age ($n = 678$). It represents an interesting distinction between data that can or could be asked from users of a free service and sensitive data that are hard to be gathered. Looking at the two important age groups, it was a general result that the older age group (35–44) was willing to gie less sensitive and non-sensitive data than the younger age group (25–34), although the difference was not significant.

In the case of online buying behaviour, respondents tend to buy physical products the most ($n = 698$), then tickets ($n = 651$), subscribe to a movie or music services ($n = 481$), and they are less frequently active in video game purchasing ($n = 164$). If the two important age groups are compared, it seems that in the case of every product category, the younger age group (25–34) tends to buy more products online than the older one (35–44), but it can be said at the same time that there was no significant difference between them.

Considering the last layer, it is interesting to analyse how much time the respondents spend on training themselves. If the two most important age groups' values are analysed, it can be seen that the younger age group (25–34) spends more time on training ($M_{25\text{-}34} = 2.78$, $SD_{25\text{-}34} = 1.071$; $M_{35\text{-}44} = 2.57$, $SD_{35\text{-}44} = 0.908$) than the older one (35–44). The significance level of the Levene's test is 0.287, so homogeneity of variance persists, and the F test of variance analysis can be conducted with enough reliability. Based on the results of the F test, in the ANOVA table, the significance level is 0.004, so the time spent on training differs based on the analysed age groups significantly. When the money spent on self-development was asked, the younger age group seemed to spend more on their self-development ($M_{25\text{-}34} = 2.66$, $SD_{25\text{-}34} = 1.249$; $M_{35\text{-}44} = 2.49$, $SD_{35\text{-}44} = 1.212$), but the difference did not seem to be significant between the two age groups. If the whole sample is viewed, there is significant difference (sig = 0.000) among the age groups, and the Levene's test is 0.000, showing homogeneity of variance, so F test can be conducted with enough reliability. In the case of money spent of self-development, there was no significant difference among the age groups in the whole sample. Our results are summarized in Table 3.

5. CONCLUSIONS

The aim of our research was to map the working digital environment. In our view, this can only be approached in a holistic way, not the way it is traditionally done in the literature by looking at only one (consumer) or the other (service provider) side.

Concluding the information processing layer of the societal dataset, interestingly no significant relationship was observed between online information sources and age categories in the sample. It is a social reflection of the continuous development of digital culture. At the same time, in case of the trust assessment of online interfaces, based on the evaluation of the entire sample, the respondents are the most distrustful with these interfaces. In case of traditional mass media and friends as information sources, significant relationships were observed only in the whole sample, but there was no significant difference between the two highlighted age categories.

In connection with online the trust literacy layer in societal sample, most respondents value the rapid development of online activities as an opportunity for the individual and society. Accordingly, 62.8% of the sample have never experienced concerns using the Internet; its distributions showed a very similar pattern for all age groups. Regarding trust in AI systems, the need for human assistance is extremely high; in each case it exceeded half of the sample. The level of trust differed across the whole sample, but there was no significant difference related to the individual analysis of the highlighted categories. The results showed, that even though the attitude of the sample towards digitalization was high, the acceptance of a new level of automation (AI technologies) was still far from the reality.

According to the results of the privacy management layer, among the predefined personal data types the same sensitivity rank emerged in the societal sample, and in the two age

Table 3. Study 2 results – Business perspective

Layer 1: Infomration processing		
Holiday planning (Q10)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V; ANOVA, F test, Levene's test***	
0–1 weeks	full sample: significant, weak relationship	between the two age categories: not significant
1–3 weeks		
4–6 weeks		
6–8 weeks		
8+ weeks		
Decision related to financial tasks (Q11)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V; ANOVA, F test, Levene's test***	
decides instantly	full sample: no significant relationship	between the two age categories: not significant
decides rather instantly		
decides in between		
collects some information		
collects a lot of information		
Information gathering sources (Q12)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V; ANOVA, F test, Levene's test***	
decides alone	full sample: no significant relationship	between the two age categories: not significant
decides rather alone		
decides in between		

(continued)

Table 3. Continued

decided rather with the help of others				
decides with the help of others				
Layer 2: Online trust literacy				
Trust in AI systems (Q6)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V; ANOVA, F test, Levene's test***			
public administration	full sample: significant relationship		between the two age categories: not significant	
medical diagnosis				
business/financial consulting				
employment consulting				
Trust in digital technologies (Q1-Q4)	***Analysis used: Crosstabulation, Pearson's Chi-Square Test, Cramer's V; ANOVA, F test, Levene's test***			
no trust	full sample: significant relationship		between the two age categories: not significant	
low trust				
medium trust				
rather high trust				
high trust				
Layer 3: Privacy management				
Privacy attitude (Q5)	***Analysis used: Frequencies***			
Most sensitive personal data types	Bank card nr.: $n = 71$	Bank account number: $n = 66$	Social security number: $n = 57$	Licence plate: $n = 117$
Least sensitive personal data types	Address: $n = 322$	Health inf.: $n = 134$	Travel inf.: $n = 300$	Age: $n = 678$
Online buxing behaviour (Q17)	***Analysis used: Frequencies, Means, ANOVA (F test, Levene's test)***			

(continued)

Table 3. Continued

buying physical products	$n = 698$		$n_{25\text{-}34} = 387$	$n_{35\text{-}44} = 311$	between the two age categories: not significant
buying tickets	$n = 651$		$n_{25\text{-}34} = 269$	$n_{35\text{-}44} = 212$	
subscribing to movie or music services	$n = 481$		$n_{25\text{-}34} = 362$	$n_{35\text{-}44} = 289$	
video game purchasing	$n = 164$		$n_{25\text{-}34} = 81$	$n_{35\text{-}44} = 83$	
Training (Q18, Q20)	***Analysis used: Means, Standard Deviation, ANOVA (F test, Levene's test)***			
time spent on training	$M_{25\text{-}34} = 2.78$	$SD_{25\text{-}34} = 1.071$	$M_{35\text{-}44} = 2.57$	$SD_{35\text{-}44} = 0.908$
	between 2 age cat.: significant relationship			
money spent on training	$M_{25\text{-}34} = 2.66$	$SD_{25\text{-}34} = 1.249$	$M_{35\text{-}44} = 2.49$	$SD_{35\text{-}44} = 1.212$
	full sample: significant relationship			

Source: authors.

categories. A recommender system requesting less sensitive data for administration supports potential customer's acquisition. The younger category showed a greater willingness to provide their personal data. From 12 listed data storage options, online interfaces tended to be the most unreliable options in the total sample, while in case of fundamentally trust-based services (e.g.: doctor's office, bank) respondents feel their personal data the most secure. The preference of older group for trust-based services is slightly higher, but the differences did not prove to be significant. In practice, this result could hinder the online access of potential customers. As respondents proved to be rather data sensitive, it was not surprising that more than two-thirds of the sample do not train themselves against the challenges of the online world. It could mean, that most of the sample is self-confident in overcoming online barriers.

According to the results from the Business Perspective dataset, there were no significant differences in the sample related to information processing or online trust literacy considering the main age groups that were in the focus of this research (25–34, 35–44), although trust in digital technologies (i.e., AI) seems to be lower in older age segments. Regarding privacy management, it seems that older age segments give less personal information to service providers than their younger counterparts, presumably because they have more concerns in this matter.

It was a huge data collection challenge that the two target groups use different concepts and approaches. In the course of our work, we combined the results of two primary data surveys in a systematization table, thus creating an interpretation model that can be used to connect the two sides. The limitation of our research is that we worked from existing databases, but based on the matrix created in this way, we can later perform a double questionnaire and data collection that better supports this. This will reduce the number of statistical refinements in the analysis.

In our research, we have created a framework that helps capture the different interests of the two target groups in one system. We have analysed the databases in detail, our further goal is to create an online trust index that can be used to characterize the online environment of a country or a region. This index will show exactly messages are the most conducive in each target group for money or information can be exchanged. With this knowledge, not only e-commerce and e-business can be developed, but also social dialogue and social awareness. As a result of our research, the interdependence of the two target groups can be described on three levels (information processing, online trust literacy, and privacy management). Further development of the six-item index and testing on other samples is the next step in our research.

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