A Comparative Empirical Study of Data Intelligence and Expert Knowledge from a Trust Perspective: Postprint

Authors: Liu Kunfeng, Li Yanhong, Zhang Xinyuan

Date: 2023-04-01T16:02:48+00:00

Abstract

[Purpose/Significance] From a trust perspective, comparing users' perceptions of data intelligence and expert knowledge helps to understand the current trust status and differences in these two typical decision information sources, thereby providing recommendations for the deepened application of data intelligence and the effective integration of data intelligence and expert knowledge. [Method/Process] Based on the classic two-dimensional division of trust, namely cognitive trust and affective trust, a measurement scale containing two pairs of four latent variables was designed. Using the questionnaire survey method, 342 valid samples were obtained, and descriptive statistics and paired-sample t-test methods were employed for data analysis. [Results/Conclusion] The study found that users' cognitive trust in data intelligence is significantly higher than that in expert knowledge, while their affective trust in data intelligence is significantly lower than that in expert knowledge.

Full Text

A Comparative Empirical Study of Data Intelligence and Expert Knowledge from the Perspective of Trust

Liu Kunfeng[1], Li Yanhong[1], Zhang Xinyuan[2]
[1]School of Information Management, Zhengzhou University of Aeronautics, Zhengzhou 450046
[2]Henan Academy of Big Data, Zhengzhou University, Zhengzhou 450052

Abstract:
[Purpose/Significance] Comparing users' perceptions of data intelligence and expert knowledge from the perspective of trust helps to understand users' current trust status and differences regarding these two typical decision-making information sources, thereby providing recommendations for the deepened application

of data intelligence and the effective integration of data intelligence with expert knowledge. [Method/Process] Based on the classic two-dimensional classification of trust—cognitive trust and emotional trust—a measurement scale was designed including two pairs and four latent variables. Using a questionnaire survey method, 342 valid samples were collected, and descriptive statistics and paired sample t-tests were employed for data analysis. [Result/Conclusion] The study found that users' cognitive trust in data intelligence is significantly higher than in expert knowledge, while their emotional trust in data intelligence is significantly lower than in expert knowledge.

Keywords: big data; artificial intelligence; data intelligence; expert knowledge; cognitive trust; emotional trust
Classification Number: G203
DOI: 10.13266/j.issn.0252-3116.2021.06.012

Big data, deep learning, and high-performance computing are propelling society into the era of data intelligence. In 2015, China implemented its national big data strategy aimed at developing and applying big data. In 2016, the AI robot AlphaGo, based on deep learning, defeated the world champion in Go, marking a milestone event where data intelligence began to rival human wisdom. In 2019, the National Science Library of the Chinese Academy of Sciences launched the English journal *Data Intelligence* to promote research and practice in the field. The implementation of national strategies such as "Intelligence+" and "New Infrastructure" provides new opportunities for the development of data intelligence. Data intelligence refers to the extraction of knowledge and manifestation of intelligence directly from big data through AI algorithms, with the ultimate goal of serving decision-making by improving decision quality, efficiency, and stability. It represents an important emerging source of decision-making information. However, despite industry and academic attention, concerns about security issues and risks associated with AI applications persist, hindering the deepened application of data intelligence. Expert knowledge, defined as the experience and skills summarized by domain experts through long-term professional learning and practice for judging events or phenomena within their field, has long served as an important traditional source of decision-making information. Nevertheless, due to the scarcity of expert resources, emerging crises of expert trust, and the increasingly personalized trends in human decision-making activities, the application of expert knowledge faces severe challenges.

Data empowerment of industries and sectors represents a social development trend. Scholars have deeply contemplated the possibilities of data intelligence applications across various domains and empirically investigated professionals' perceptions and attitudes toward its application, seeking pathways for deepened application. Both data intelligence and expert knowledge are decision-oriented and exist in a competitive relationship, yet their deep integration is considered the optimal solution and future direction for handling complex decision-making problems. To promote their integrated development, a new round of "human-machine" intelligence competition has begun. Various comparative studies and human-machine competitions have thoroughly examined the relative strengths and weaknesses of AI systems empowered by data versus human experts in predicting, recognizing, judging, or detecting objects, events, or phenomena. However, existing research has largely neglected ordinary users' perceptions and attitudes toward data intelligence, while comparative studies of data intelligence and expert knowledge have focused primarily on performance differences in decision-making applications, largely overlooking users' perceptual differences, particularly regarding trust.

2 Literature Review

2.1 Data Intelligence and Expert Knowledge

2.1.1 Data Intelligence: Application Trends and Challenges Definitions of data intelligence present multiple perspectives. From a technical viewpoint, industry representatives such as Baidu define data intelligence as the fusion of big data and AI technologies to mine and analyze massive datasets, discover valuable information and knowledge embedded in data, endow data with intelligence, and build models to seek solutions to existing problems, enabling predictions about objects, events, or phenomena. From a management perspective, scholars view data intelligence as predictive analytics technologies—including big data mining, machine learning, and deep learning—that extract valuable, actionable information or knowledge from multi-source heterogeneous big data inside and outside real-world application scenarios to enhance management and decision-making levels for complex practical activities. From a knowledge discovery perspective, scholars consider data intelligence as the manifestation of intelligence through algorithms that directly parse knowledge from structured and unstructured big data, with the ultimate goal of discovering new knowledge. The application purpose of data intelligence is to serve decision-making, including improving decision quality, efficiency, and stability, and replacing repetitive decisions. Regardless of perspective, data intelligence ultimately presents as information and knowledge that assists decision-making subjects, representing an AI-generated emerging decision-making information source. The core paradigm of data intelligence generation is "data + AI algorithms + computing power + scenarios," where data serves as raw material, algorithms provide computational thinking, computing power offers operational support, and scenarios provide demand traction. Naturally, the realization of data intelligence also relies on rules of expert knowledge in determining reliable information sources, selecting appropriate AI algorithms, allocating sufficient computing capacity, and identifying suitable application scenarios.

With the normalization of large-scale data and continuous improvement in computing power, research on data intelligence applications has attracted significant academic attention. Literature reviews reveal that data intelligence application research targets not only critical domains such as infectious disease monitoring and early warning, disease diagnosis, and stock market trend prediction, but also general domains like nutritional dietary decision-making, tourism product evaluation, and exploratory conversation identification in MOOC forums. Once implemented, these applications serve not only professional decision-makers such as government leaders, doctors, and enterprise managers, but also non-professional decision-makers like random users, consumers, teachers, and students. It is foreseeable that future data intelligence applications will expand to more domains and broader populations, becoming a new option for human decision-making activities.

Industry and academia recognize the application prospects of data intelligence. However, the *2020 Artificial Intelligence Development Report White Paper* released by New H3C Group shows that people are generally concerned about security issues in the popularization of AI applications, including risks of user privacy leakage, platform and model leakage, authenticity of AI system input data, and security of AI infrastructure and architecture processes. Empirical studies also reveal pessimistic attitudes toward data intelligence applications. T. Q. Sun and R. Medaglia found that government decision-makers and hospital managers/doctors generally believe that the public's limited understanding of AI may lead to a lack of trust in data intelligence-based decisions. A. M. Cox et al. found that library thought leaders believe university libraries may face numerous challenges in applying data intelligence, including ethical issues in data collection, data quality and security issues, and decision comprehensibility problems. M. Wiesenberg and R. Tench found that communication professionals in Central and Eastern Europe believe using social robots to mine social media data for identifying opinion leaders poses significant ethical challenges, with only 11.5% of organizations currently using or planning to use social robots. These findings indicate that since data intelligence is not yet widely applied, existing empirical studies are based only on respondents' intuitions rather than actual usage experiences. Moreover, most studies focus on professionals as survey subjects, largely neglecting ordinary users. The deepened application of data intelligence requires broad participation from ordinary users, making it necessary to understand their perceptions and attitudes.

2.1.2 Expert Knowledge and Application Challenges In academic discourse, experts typically refer to domain experts who have mastered knowledge in a particular field, possess unique insights, and have specialized knowledge, experience, and skills in practical activities within that field. Expert knowledge is the knowledge of domain experts—experience and skills summarized through long-term professional learning and practice for judging events or phenomena within their domain. Expert knowledge is generally considered highly credible and authoritative and has long served as an important traditional decision-making information source widely involved in human decision-making activities. Common decision-making methods such as the Delphi method, brainstorming, and expert meetings primarily rely on expert knowledge. Expert systems that simulate human expert decision-making processes using expert knowledge and experience revitalized frustrated AI in the 1980s and continue to be used today.

However, several challenges make expert knowledge increasingly difficult to apply in decision-making. First, expert resources are scarce, making it difficult for decision-making subjects to identify, select, and evaluate domain experts. Second, the expert trust crisis has become fully apparent. The *China Residents' Social Trust Survey Report* released by the Social Survey Center of Shanghai Jiao Tong University shows that nearly half of respondents do not trust expert opinions. Third, with rapid social development, new things, phenomena, and problems continue to emerge, making it difficult to meet users' increasingly diversified, personalized, and complex decision-making needs by relying solely on expert knowledge.

2.2 Comparative Research on Data Intelligence and Expert Knowledge

Since the birth of AI in the 1950s, comparisons between AI and human intelligence have erupted periodically, but all ended with AI cooling down due to limitations in computing power and trainable data volume. Since 2012, high-performance computing and large-scale data have become normalized, and the deep learning revolution has swept the AI field. AI systems empowered by data can achieve more human-like cognitive capabilities, propelling the arrival of the data intelligence era. Comparisons between AI and human intelligence have once again become social hotspots, with comparison objects shifting from ordinary people to experts. Numerous studies have focused on the relative advantages and disadvantages of data intelligence and expert knowledge in decision-making activities.

S. Biswal et al. used a deep learning model to mine and analyze sleep EEG data, reproducing diagnoses of sleep staging, sleep apnea, and limb movement, and found diagnostic accuracy comparable to human experts. A. Singh et al. used convolutional neural networks to build a computer vision algorithm for automatic hand hygiene detection, finding 96.8% consistency with human auditors' observations. S. S. Chaturvedi et al. built a skin cancer diagnosis system based on deep convolutional neural networks and found its diagnostic accuracy superior to dermatology experts. These comparative studies focus on performance differences between data intelligence and expert knowledge in decision-making applications, confirming that the former's performance has reached or even exceeded the latter's. However, they largely neglect users' perceptual differences between the two, particularly regarding trust—the most basic and important perception. For a long time, people's identification with knowledge has depended on trust rather than truth. Comparing users' perceptual differences from the trust perspective helps reveal the positions of both in users' minds and provides references for their future deployment.

2.3 Trust in User-Information Source Interaction

Trust is an important factor in social relationships. In recent years, scholars have extensively examined the role of trust in user interactions with various information sources. Wang Xiaoning and Liu Lili found that the more farmers trust precision information service providers, the more willing they are to use precision information services. C. G. Huo et al. found that users' trust in health knowledge publishers on social media significantly influences their health knowledge adoption behavior. M. Asraf et al. found that if consumers continuously trust online product recommendation information, they will continue using it for purchase decisions. Sun Yuwei et al. believe that researchers' trust in scientific data is a key factor affecting their data reuse behavior. Fang Aihua et al. found that users' trust in virtual community knowledge products significantly influences their knowledge payment willingness. These findings show that the more users trust information providers or content from specific sources, the more inclined they are to adopt and use the information and make behavioral changes accordingly.

In this study, data intelligence and expert knowledge are decision-making information sources generated by AI and experts, respectively. Using data intelligence or expert knowledge for decision-making requires users to bear risks such as privacy leakage, knowledge failure, or unsatisfactory decisions. Users inevitably have positive expectations for AI or experts and the decision-making information they generate—this expectation is trust. Based on existing literature, it is reasonable to argue that the more users trust data intelligence or expert knowledge, the more willing they are to apply both for decision-making. D. J. McAllister divided trust into two dimensions: cognitive trust and emotional trust. Cognitive trust originates from the trustor's cognitive judgment of the trustee's key characteristics such as competence and reliability, relying more on empirical evidence. Emotional trust stems from emotional connections between trustor and trustee, such as emotional attachment and bonding, relying on subjective perception and judgment. Based on this classic dimensional division, scholars have extensively examined the role of cognitive and emotional trust in user-information source interactions. Dong Ying et al. studied users' willingness to respond to social network product recommendations, finding that both cognitive and emotional trust in contacts significantly and positively influence response willingness. H. M. Fan and R. Lederman studied online health community users' information adoption behavior, finding that if users develop cognitive and emotional trust in information contributors, they are more inclined to accept the contributors' advice. K. C. Chang et al. studied consumer purchase behavior in social media contexts, finding that both cognitive and emotional trust in social media effectively predict purchase intention. These findings demonstrate that cognitive and emotional trust are equally important in user-information source interactions.

In this study, users' trust in data intelligence or expert knowledge also includes cognitive and emotional trust. The former is based on users' cognitive judgments about the usefulness, credibility, reliability, and ability to meet their needs of both sources. The latter is based on users' experiential feelings, sense of security, pleasure, and satisfaction when applying both sources. It is reasonable to argue that only when users achieve undifferentiated trust in data intelligence and expert knowledge in both cognitive and emotional dimensions can they possibly integrate both for decision-making. Existing research mostly focuses on the role of cognitive and emotional trust in single information source contexts, with few studies comparing users' trust perceptions of two distinct yet competitive information sources based on these two dimensions. This study compares and reveals users' trust perceptions and differences regarding data intelligence and expert knowledge from the perspectives of cognitive and emotional trust, providing direction for the deepened application of the former and effective integration of both.

3 Research Methods

3.1 Questionnaire Design

Using data intelligence for decision-making essentially means using AI big data mining and analysis results for decision-making. To improve questionnaire comprehensibility, "AI data mining results" was used to refer to "data intelligence." This study designed four latent variables: cognitive trust in AI data mining results (CTDM), emotional trust in AI data mining results (ETDM), cognitive trust in expert knowledge (CTEK), and emotional trust in expert knowledge (ETEK). All latent variables referenced mature scales and were appropriately adapted to the research context. Specifically, the cognitive and emotional trust scales were designed based on the work of D. J. McAllister and H. M. Fan and R. Lederman. After completing the initial questionnaire draft, a small-scale pre-test was conducted. Based on pre-test results, language expressions were adjusted to enhance comprehensibility. A 7-point Likert scale (1 = "strongly disagree," 4 = "uncertain," 7 = "strongly agree") was used for measurement.

3.2 Data Collection

University students were selected as the survey population due to their strong cognitive abilities and sensitivity to cutting-edge fields, enabling them to accurately grasp the research context. Additionally, university-educated students are more likely to become actual users of data intelligence in the future, making them more likely to resonate with this study. Data intelligence applications in disease diagnosis started early and have gained certain social recognition. As early as 2017, AI imaging robots competed on CCTV's "Super Brain" program with experienced radiologists, becoming familiar to audiences. The questionnaire incorporated the disease diagnosis context, providing application examples of AI data mining results and expert knowledge: (1) With support from deep learning algorithms and high-performance computing, AI imaging robots mine and analyze medical imaging data such as MRI, CT, and ultrasound images to provide disease diagnosis results; (2) Specialists observe and analyze MRI, CT, and ultrasound images based on clinical experience to provide disease diagnosis results. Respondents were asked to answer based on similar experiences; those without direct experience answered based on subjective perception.

An online questionnaire was created using Wenjuanxing and distributed through WeChat groups, Moments, QQ groups, and online forums, inviting university students to participate. The questionnaire collection lasted approximately two weeks, yielding 513 responses. Invalid questionnaires with completion times under 60 seconds or consistent answers across all questions were removed, resulting in 342 valid samples. Sample characteristics are shown in Table 1 .

4 Data Analysis and Results

Data analysis addressed three questions: Q1: What are the precise data distributions of cognitive and emotional trust for data intelligence and expert knowledge? Q2: Which source do users have higher cognitive trust in and which do they have higher emotional trust in? Q3: What are the exact differences in users' cognitive and emotional trust between data intelligence and expert knowledge?

4.1 Measurement Model Testing

Before data analysis, the reliability and validity of the measurement model were assessed, including evaluations of reliability, content validity, convergent validity, and discriminant validity. All latent variables referenced mature scales and were appropriately adjusted based on the pre-test, ensuring the scales were clear and explicit—thus possessing content validity.

Table 2 shows the measurement model's Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). As shown in Table 2, all latent variables' Cronbach's alpha and CR values exceed the minimum threshold of 0.7, indicating good reliability. All latent variables' AVE values exceed the minimum threshold of 0.5, indicating convergent validity. To test discriminant validity, the square roots of latent variables' AVE values were compared with inter-variable correlation coefficients. Table 3 shows that all latent variables' AVE square roots (italicized diagonal values) exceed their correlation coefficients with other variables, indicating discriminant validity.

Given the measurement model's reliability and validity, the data can be used for further analysis. Specifically, the discriminant validity demonstrates that the four latent variables are independent, making meaningful the comparison of users' cognitive and emotional trust differences between data intelligence and expert knowledge. Meanwhile, the model's reliability and convergent validity enable structural-level data analysis.

4.2 Comparison of Users' Cognitive Trust in Data Intelligence and Expert Knowledge

Users' cognitive trust in data intelligence or expert knowledge indicates they perceive high application value and reliability that can meet their decision-making needs. For variable CTDM, respondents rated the following items: (1) AI data mining can provide me with scientific decision-making solutions; (2) AI data mining results are trustworthy; (3) AI data mining results are very reliable; (4) AI data mining results can meet my needs. A 7-point Likert scale measured these items. For the 342 samples, the number of respondents selecting each point (1-7) was calculated for each item. Since the latent variables demonstrated reliability and convergent validity, the total number of selections for each point across the four items was calculated as the subtotal for CTDM at each score level. CTDM's total number of scores was 1,368 (342×4).

For variable CTEK, respondents rated the same items. The same counting method calculated CTEK's subtotals at each score level. Figure 1 [Figure 1: see original paper] shows the comparison of users' cognitive trust in data intelligence and expert knowledge.

Figure 1 reveals that 75.51% (1,033/1,368) of respondents have cognitive trust in data intelligence, while 67.18% (919/1,368) have cognitive trust in expert knowledge. Meanwhile, 4.53% (62/1,368) lack cognitive trust in data intelligence, and 8.33% (114/1,368) lack cognitive trust in expert knowledge. For CTDM and CTEK, the proportions selecting the neutral point (4) were 19.96% (273/1,368) and 24.49% (335/1,368), respectively, indicating neutral attitudes toward data intelligence and expert knowledge regarding cognitive trust.

4.3 Comparison of Users' Emotional Trust in Data Intelligence and Expert Knowledge

Users' emotional trust in data intelligence or expert knowledge indicates they feel positively about using them and have relatively close emotional connections. For variable ETDM, respondents rated: (1) I feel good about AI data mining results; (2) I feel at ease using AI data mining results for decision-making; (3) I feel satisfied using AI data mining results for decision-making; (4) My mood improves when obtaining AI data mining results. The same method was used to analyze ETDM and ETEK's data structures. Figure 2 [Figure 2: see original paper] shows the emotional trust comparison.

Figure 2 shows that 67.4% (922/1,368) of respondents have emotional trust in data intelligence, while 76.24% (1,043/1,368) have emotional trust in expert knowledge. Meanwhile, 18.57% (254/1,368) lack emotional trust in data intelligence, and only 4.61% (63/1,368) lack emotional trust in expert knowledge. For ETDM and ETEK, neutral selection proportions were 14.04% (192/1,368) and 19.15% (262/1,368), respectively.

4.4 Paired Sample t-test

Figures 1 and 2 show precise data distributions for cognitive and emotional trust, answering Q1. They also indicate differences in users' cognitive and emotional trust between data intelligence and expert knowledge. To accurately demonstrate these differences and answer Q2 and Q3, paired sample t-tests compared sample means.

Table 4 results show significant differences in both cognitive and emotional trust. Specifically, mean cognitive trust in data intelligence and expert knowledge were 5.129 and 4.906, respectively, with a mean difference of 0.223 ($p < 0.001$), indicating significantly higher cognitive trust in data intelligence. Mean emotional trust in data intelligence and expert knowledge were 4.731 and 5.179, respectively, with a mean difference of -0.448 ($p < 0.001$), indicating significantly lower emotional trust in data intelligence.

5 Discussion

Data intelligence and expert knowledge are two important yet competitive decision-making information sources with distinct characteristics that are beginning to influence people's information-seeking behavior for decision-making. Data intelligence originates from AI systems' mining and analysis of objective data, presenting rational results, while expert knowledge stems from experts' long-term observation and reflection on domain matters, presenting results with emotional coloring. Understanding their current positions in users' minds is worth exploring. This study compares users' cognitive and emotional trust in data intelligence and expert knowledge. Figures 1 and 2 present precise data distributions, supplemented by paired sample t-tests in Table 4. This research offers theoretical and practical implications but also has limitations.

5.1 Theoretical Implications

Rapidly evolving information technology and complex, changing information environments increase uncertainty in human information activities, making trust a key factor in human-technology and human-environment interactions. Many scholars have examined trust issues regarding specific information sources from cognitive and emotional trust dimensions, focusing mostly on how these trusts form, what factors influence them, and how they affect user attitudes, intentions, and behaviors. Few studies have compared users' trust perceptions of different information sources based on these two dimensions. This study provides a new perspective for trust theory application by comparing users' cognitive and emotional trust in data intelligence and expert knowledge. While expert knowledge has long provided important decision-making references and remains indispensable despite some skepticism, data intelligence is an emerging source whose application value has gained preliminary recognition but still requires practical testing in more decision-making activities. The confrontation, collision, complementarity, and integration of data intelligence and expert knowledge will be important future research areas. This study reveals that users currently have significantly higher cognitive trust but lower emotional trust in data intelligence compared to expert knowledge, providing new directions for future research, such as exploring how to improve emotional trust in data intelligence and cognitive trust in expert knowledge, and systematically revealing both sources' positions from more perspectives.

5.2 Practical Implications

Under the development trend of intelligence-driven intelligence analysis and smart intelligence services, expert knowledge will inevitably be replaced by data intelligence in some domains. However, Table 1 shows that 78.07% of respondents prefer to trust the integration of AI data mining results and expert knowledge, indicating users currently prefer integrated application for decision-making. Therefore, promoting deepened data intelligence application and its effective integration with expert knowledge is an important practical issue.

Figure 2 shows more users have emotional trust in expert knowledge than in data intelligence. Table 4 confirms that emotional trust in data intelligence is significantly lower than in expert knowledge, with ETDM having the lowest mean (4.731) and ETEK the highest (5.179). This suggests users have less emotional connection with data intelligence, possibly because most people still understand it from a technical perspective—as a product of complex, cold technologies like big data and AI—lacking affinity for the technology and thus emotional connection to its products. In contrast, people have more comprehensive cognition of experts and have established stable relationships over time, making emotional acceptance of expert knowledge easier. Research confirms that emotional reactions influence user information behavior even more than cognitive reactions. Therefore, enhancing users' emotional connection with data intelligence facilitates its deepened application. Emotional connections most commonly and easily occur between people, based on mutual understanding, maintained contact, and genuine care. Recommendations include: (1) further advancing the anthropomorphic presentation of data intelligence, such as embedding AI systems in humanoid robots that mimic human language and body movements; (2) appropriately endowing AI systems with emotional capabilities while continuously improving their professional competence, such as using computer vision to recognize users' real-time emotions for contextualized services; (3) strengthening user education to help them systematically understand data intelligence generation and mechanisms; and (4) developing more data intelligence products that participate in daily human life, enabling users to actively establish stable connections with AI systems, improving development targeting and personalization, and making users feel genuinely cared for and exclusive.

Figure 1 shows more users have cognitive trust in data intelligence than expert knowledge. Table 4 confirms significantly higher cognitive trust in data intelligence, reflecting the expert trust crisis. This may result from: (1) uneven expert quality and the social consensus that some experts are incompetent or influenced by social relationships and personal emotions, leading to subjective deviations; and (2) the established paradigm of discovering knowledge from big data, whose value is recognized. Achieving undifferentiated trust is the foundation for effective integration—data intelligence needs enhanced emotional trust, while expert knowledge needs enhanced cognitive trust. Recommendations for improving cognitive trust in expert knowledge include: (1) optimizing expert identification, selection, and evaluation mechanisms to accurately identify "true" experts and timely eliminate "unqualified" ones; (2) establishing norms and guidelines to standardize and direct expert knowledge generation and application, ensuring content and service quality; and (3) experts themselves should transform their mindset, enhance service awareness, systematically understand users' personalized needs, and meet them targeted.

5.3 Limitations and Future Directions

This study has limitations: (1) It treats data intelligence and expert knowledge as two typical decision-making information sources, comparing users' trust perceptions overall without limiting application or knowledge domains, potentially reducing result specificity. Future research could examine perceptual differences in specific domains. (2) Data intelligence application is still in its early stages with limited user experience. This study used questionnaires requiring experienced users to answer based on experience and inexperienced users on subjective perception, potentially reducing accuracy and systematicity. Future research could target users with real data intelligence experience and employ multiple methods. (3) This study used university students, who generally have higher acceptance of new things, potentially limiting generalizability. Future research could expand the population for more accurate, generalizable conclusions.

References

[1] Zhao Xing, Qiao Lili, Ye Ying. Cross-boundary expansion of library and information science toward data intelligence and knowledge discovery: Integration of data, academia, and creation [J]. *Journal of Library Science in China*, 2020, 46(6): 16-25.

[2] Ye Ying. Academic thought and technical methods of library and information science and their innovation [J]. *Journal of Library Science in China*, 2019, 45(2): 15-25.

[3] Ding Xiaowei, Su Xinning. Financial security intelligence analysis based on blockchain-enabled trustworthy big data AI [J]. *Journal of the China Society for Scientific and Technical Information*, 2019, 38(12): 1297-1309.

[4] Guo Hailing, Ma Hongyu, Xu Zehui. Modeling and empirical study of social media users' information disclosure intention: A WeChat user example [J]. *Library and Information Service*, 2019, 63(15): 111-120.

[5] Zhang Weiwei, Bai Lu. Research on users' continuous usage behavior in crowdsourcing communities: Based on ECM-ISC and commitment-trust theory [J]. *Information and Documentation Services*, 2017(2): 54-61.

[6] Baidu Baike. Data intelligence [EB/OL]. [2020-08-07]. https://baike.baidu.com/item/%E6%95%B0%E6%8I

[7] Zhan Qinglong, Yang Jingjing. Research on the transition of classroom teaching management supported by data intelligence [J]. *E-Education Research*, 2020, 41(7): 100-107.

[8] Wu Junjie, Liu Guannan, Wang Jingyuan, et al. Data intelligence: Trends and challenges [J]. *Systems Engineering-Theory & Practice*, 2020, 40(8): 2116-2149.

[9] TalkingData Mobile Observatory. 2018 Data intelligence ecosystem report [R/OL]. [2020-08-07]. http://mi.talkingdata.com/report-detail.html?id=843.

[10] Tang Xiaobo, Zheng Du, Zhai Xiapu. Competitive intelligence system model based on big data intelligence [J]. *Information Studies: Theory & Application*, 2018, 41(11): 133-137, 160.

[11] Serban O, Thapen N, Maginnis B, et al. Real-time processing of social media with SENTINEL: A syndromic surveillance system incorporating deep learning for health classification [J]. *Information Processing & Management*, 2019, 56(3): 1166-1184.

[12] Li L S. Deep adversarial model for musculoskeletal quality evaluation [J]. *Information Processing & Management*, 2020, 57(1): 102146.

[13] Maqsood H, Mehmood I, Maqsood M, et al. A local and global event sentiment based efficient stock exchange forecasting using deep learning [J]. *International Journal of Information Management*, 2020, 50: 432-451.

[14] Kim J C, Chung K Y. Knowledge-based hybrid decision model using neural network for nutrition management [J]. *Information Technology and Management*, 2019: 1-11.

[15] Ma Chao, Li Gang, Chen Sijing, et al. Research on usefulness identification of online tourism reviews based on multi-modal data semantic fusion [J]. *Journal of the China Society for Scientific and Technical Information*, 2020, 39(2): 199-207.

[16] Dong Qingxing, Li Huayang, Cao Gaohui, et al. Research on exploratory conversation identification method in MOOC forums based on deep learning [J]. *Library and Information Service*, 2019, 63(5): 92-99.

[17] 199IT. New H3C: 2020 Artificial intelligence development report white paper [R/OL]. [2020-12-20]. http://www.199it.com/archives/1050916.html.

[18] Sun T Q, Medaglia R. Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare [J]. *Government Information Quarterly*, 2019, 36(2): 368-383.

[19] Cox A M, Pinfield S, Rutter S. The intelligent library: Thought leaders' views on the likely impact of artificial intelligence on academic libraries [J]. *Library Hi Tech*, 2019, 37(3): 418-429.

[20] Wiesenberg M, Tench R. Deep strategic mediatization: Organizational leaders' knowledge and usage of social bots in an era of disinformation [J]. *International Journal of Information Management*, 2020, 51: 102042.

[21] Ma Jie, Wu Qiong, Cui Chun. Research on the mechanism of domain expert knowledge in semi-automatic ontology construction [J]. *Library and Information Service*, 2011, 55(23): 17-21.

[22] Liu Liu, Wang Dongbo, Huang Shuiqing. Review of artificial intelligence research from a machine learning perspective and its impact on library and information science [J]. *Library and Information*, 2017(6): 84-95.

[23] Xu Pengcheng, Bi Qiang. Research on domain expert identification based on knowledge supernetworks [J]. *Data Analysis and Knowledge Discovery*, 2019, 3(11): 89-98.

[24] Guo Fei, Sheng Xiaoming. The crisis and reconstruction of expert trust [J]. *Studies in Science of Science*, 2016, 34(8): 1131-1136.

[25] Xie Yungeng, Wan Xuan'ao, Liu Lu, et al. China residents' social trust survey report [J]. *New Media and Society*, 2017(1): 7-21.

[26] Zhou Qun, Hua Bolin. Research on identification of science and technology decision-making demand themes based on multi-source data fusion [J]. *Information Studies: Theory & Application*, 2019, 42(3): 107-113.

[27] Schuetz S, Venkatesh V. Research perspectives: The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction [J]. *Journal of the Association for Information Systems*, 2020, 21(2): 460-482.

[28] Biswal S, Sun H Q, Goparaju B, et al. Expert-level sleep scoring with deep neural networks [J]. *Journal of the American Medical Informatics Association*, 2018, 25(12): 1643-1650.

[29] Singh A, Haque A, Alahi A, et al. Automatic detection of hand hygiene using computer vision technology [J]. *Journal of the American Medical Informatics Association*, 2020, 27(8): 1316-1320.

[30] Chaturvedi S S, Tembhurne J V, Diwan T. A multi-class skin cancer classification using deep convolutional neural networks [J]. *Multimedia Tools and Applications*, 2020, 79(39): 28477-28498.

[31] Wang Xiaoning, Liu Lili. Research on influencing factors of rural precision information service diffusion from supply-demand perspectives [J]. *Information Science*, 2020, 38(3): 93-100.

[32] Huo C G, Zhang M, Ma F C. Factors influencing people's health knowledge adoption in social media [J]. *Library Hi Tech*, 2018, 36(1): 129-151.

[33] Asraf M, Ahmad J, Sharif W, et al. The role of continuous trust in usage of online product recommendations [J]. *Online Information Review*, 2020, 44(4): 745-766.

[34] Sun Yuwei, Cheng Ying, Xie Juan. Research on researchers' data reuse behavior: Systematic review and meta-synthesis [J]. *Journal of Library Science*

in China, 2019, 45(3): 110-130.

[35] Fang Aihua, Lu Mengmeng, Liu Kunfeng. Empirical study on virtual community users' knowledge payment intention [J]. *Library and Information Service*, 2018, 62(6): 105-115.

[36] McAllister D J. Affect- and cognition-based trust as foundations for interpersonal cooperation in organizations [J]. *Academy of Management Journal*, 1995, 38(1): 24-59.

[37] Yang Fu, Liu Jun, Wang Ting, et al. The "boundary dilemma" mechanism in Chinese employees' career development: The perspective of job insecurity [J]. *Nankai Business Review*, 2019, 22(6): 176-187.

[38] Dong Ying, Xu Zhengliang, Liu Fang, et al. Research on mobile social network users' willingness to respond to product recommendation information [J]. *Library and Information Service*, 2016, 60(23): 111-118.

[39] Fan H M, Lederman R. Online health communities: How do community members build the trust required to adopt information and form close relationships? [J]. *European Journal of Information Systems*, 2018, 27(1): 62-89.

[40] Chang K C, Hsu Y T, Hsu C L, et al. Effect of tangibilization cues on consumer purchase intention in the social media context: Regulatory focus perspective and the moderating role of perceived trust [J]. *Telematics and Informatics*, 2019, 44: 101265.

[41] Straub D, Boudreau M C, Gefen D. Validation guidelines for IS positivist research [J]. *Communications of the Association for Information Systems*, 2004, 13(1): 380-427.

[42] Luo Liqun, Li Guangjian. Smart intelligence services and knowledge fusion [J]. *Information and Documentation Services*, 2019, 40(2): 87-94.

[43] Qiu Yunfei, Li Chunwang. Intelligent intelligence analysis models: Data-driven and knowledge-driven [J]. *Information Studies: Theory & Application*, 2020, 43(2): 28-34.

[44] Zha Xianjin, Zhang Jinchao, Yan Yalan. Research on factors influencing users' academic information seeking behavior in Weibo: Dual-path perspective of information quality and source credibility [J]. *Journal of Library Science in China*, 2015, 41(3): 71-86.

Author Contributions:
Liu Kunfeng: Research design and writing;
Li Yanhong: Data collection and revision;
Zhang Xinyuan: Revision.

A Comparative Empirical Study on Data Intelligence and Expert Knowledge from the Perspective of Trust

Liu Kunfeng[1], Li Yanhong[1], Zhang Xinyuan[2]
[1]School of Information Management, Zhengzhou University of Aeronautics, Zhengzhou 450046
[2]Henan Academy of Big Data, Zhengzhou University, Zhengzhou 450052

Abstract: [Purpose/significance] Comparing users' perceptions of data intelligence and expert knowledge from the perspective of trust helps to understand users' current trust status and differences regarding these two typical decision-making information sources, and then provides suggestions for the deepened application of data intelligence and the effective integration of data intelligence and expert knowledge. [Method/process] Based on the classic two-dimensional classification of trust, namely cognitive trust and emotional trust, a measurement scale including two pairs and four potential variables was designed. A questionnaire survey was used to obtain 342 valid samples, and descriptive statistics and paired sample t-test methods were used for data analysis. [Result/conclusion] The study found that users' cognitive trust in data intelligence is significantly higher than that in expert knowledge, while users' emotional trust in data intelligence is significantly lower than that in expert knowledge.

Keywords: big data; artificial intelligence; data intelligence; expert knowledge; cognitive trust; emotional trust