Exploring The Role of Both Online and Offline Knowledge Sources and Artificial Intelligence in Information Management for Digital Libraries

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Abstract

With growing emphasis on technologies in different fields, including the libraries, the implications and utilization of artificial intelligence in operations has become crucial. The objective of this study is to examine the intricate relationships between two types of knowledge sharing (online and offline) and artificial intelligence in the information management context for digital libraries in China. Using this context, the data was collected from 310 respondents across different digital libraries over 13 weeks. Findings provide a platform for fascinating debate using three key dimensions of information management: information quality, information security, and information technology. Besides, studying the impact of online knowledge sharing on information security, the study also affirms that improvement in three dimensions of information management is mainly attributed to online and offline knowledge sharing and artificial intelligence for digital libraries across China. These results provide immense and significant implications for decision-makers linked with digital libraries while observing online and offline knowledge sharing and artificial intelligence and their connection to information management. The study further emphasizes addressing the limitations in the final sections for future studies.

Keywords

Information Management, Information Security, Information Technology, Information Quality, Artificial Intelligence, Knowledge Sharing.

1. Introduction

Information management is a strategic decision-making approach that systematically collects, organizes, and uses information to support the organization's strategic objectives and goals (**Aslan**, 2020; **Robson**, 1997; **Choo**, 2002). Information management encompasses a wide range of activities like information retrieval (**Nie**, 2022), information and data governance (**Mikalef *et al.***, 2020), keeping the quality of data, data security, and focusing on the technological perspective (**Bolisani; Scarso**, 1999) which seems integral for any organization. The effective information management not only improves operational efficiency but also provides a competitive advantage. In the current digital world, managing information has become more important than ever as organizations handle larger amounts of data and tackle issues under the title of cybersecurity threats, meeting regulations, and adapting to new technologies (**Dalkir**, 2013). Several studies have focused on the significance of information management, further expanding the understanding of this field. **Azeroual *et al.*** (2021) focused on implementing and user acceptance of information management. The study further expanded the debate about highlighting individuals' challenges within the organization's digital environment.

Knowledge management and information management are closely linked fields that have a substantial role in the organizational work setting in the modern day. While the prime focus of information management is to deal with the collection, storage and distribution of information and data (**Franks**, 2013), knowledge management aims to build such facilities by creating and sharing the knowledge meaningfully (**Du Plessis**, 2007). Therefore, information and knowledge management provide a solid base for strategic decision-making and driving innovation. When the context of knowledge sharing in the form of both online and offline as independent variables (**Charband; Jafari Navimipour**, 2016), and information management and dependent variables, the relationship can be conceptualized in easier ways. However, this contextual relationship needs clarification on knowledge sharing and information management types. Online knowledge sharing refers to the sharing of knowledge by using different technologies, digital tools, and platforms.

On the other hand, offline knowledge sharing is mainly connected with face-to-face interaction, meetings, and traditional communication methods, fostering individuals' deeper connections. Online knowledge sharing enhances information management by improving information quality from several perspectives. The online and digital platforms allow for real-time updates, ensuring data accuracy (**Azeroual *et al.***, 2021). It also strengthens information security by enabling encrypted channels and access controls to protect sensitive information during sharing (**Enholm *et al.***, 2022). Additionally, knowledge sharing also upgrades information technology by leveraging advanced tools and systems to store, retrieve, and share knowledge efficiently. Besides, it also fosters seamless collaboration among different parties.

This modern age of technological advancement has created several benefits to societies and industries. One of the technological transformations has been experienced in the shape of artificial intelligence, which has countless implications for both social and economic activities. Like other domains, artificial intelligence is equally important in information management (**Yadav *et al.***, 2024). Artificial intelligence has removed several traditional institutional barriers and provides new growth models due to efficient data redistribution, eliminating the conventional managerial models. However, due to consistent improvement in the domain of artificial intelligence, several enterprises consider that it is just a technical change. Nevertheless, such technological change has changed the decision-making process, operating models, and organizational strategies (**Wang *et al.***, 2024). However, past studies remain silent for checking the impact of artificial intelligence on information management using the dimensions of information quality, information security, and information technology, taking the sample from the digital libraries in China. The study developed the following research questions to be addressed in this study: (1) How does online and offline knowledge sharing influence the information quality, security, and technology dimensions of China's digital libraries? (2) What is the influence of artificial intelligence on the information quality, security, and technology dimensions of China's digital libraries?

2. Review of Literature

Knowledge sharing has positively impacted the education and business sectors (**Tamjidyamcholo *et al.***, 2014). However, many professional virtual communities have been observed to struggle due to members' reluctance to share knowledge. Moreover, it is unclear whether sharing knowledge in information security effectively reduces risks. **Tamjidyamcholo *et al.*** (2014) argue that limited empirical research addresses how knowledge sharing impacts risk reduction in such communities. The study introduces a model with two key components. First, identifying and encouraging factors influencing knowledge-sharing behaviour among professional virtual communities. Second, it examines the link between knowledge sharing and the expectation of reduced security risks where the information security title has been focused. The study data from 142 LinkedIn information security group members was analyzed using the statistical tools like PLS. The findings reveal that perceived consequences, emotions, and supportive conditions significantly influence knowledge-sharing behaviour. However, social factors appear to have no substantial impact on such knowledge-sharing. The results highlight a strong, positive connection between knowledge-sharing behaviour and the expectation of reduced information security risks for the targeted sample. This insight emphasizes the value of fostering knowledge-sharing practices to enhance security results.

Knowledge sharing is crucial in knowledge management systems, as prescribed by **Tamjidyamcholo *et al.*** (2013). Sharing security knowledge significantly reduces risks and lowers investment in information security. However, research focusing on knowledge sharing in the security profession remains limited and needs a detailed investigation. **Tamjidyamcholo *et al.*** (2013) examines key factors influencing the intention of information security professionals to share knowledge. These factors include attitude, self-efficacy, trust, reciprocity norms, and shared language. The research surveyed professionals involved in virtual communities, the Society of Information Risk Analysts, and LinkedIn security groups. The study data was analyzed using the Confirmatory Factor Analysis (CFA) and Structural Equation Modelling. The findings unveil that the research model fits the data well. Results of this research showed a strong relationship between selected determinants of the intention to share knowledge.

Information sharing and Information quality have also been examined in the supply chain domain (**Li; Lin**, 2006). This study investigates how environmental uncertainty, intra-organizational factors, and inter-organizational relationships affect supply chain management information sharing and quality dynamics. Data collected from 196 organizations was analyzed using multiple regression. The findings reveal that trust in supply chain partners and a shared vision between partners positively impact both quality and information sharing, while supplier uncertainty has a negative effect. Additionally, discriminant validity analysis of key factors like information quality and sharing have their substantial differentiation to each other and other factors of the same study. These results emphasize the importance of trust, shared goals, and supplier management in enhancing the information quality and sharing practices in the supply chain domain.

As explained in the introductory sector, artificial intelligence and its connectivity with the information management domains are emerging daily. The literature also tries to show similar evidence. **Hlávka** (2020) explores the key issues in security, privacy, and information sharing, which is considered an AI-based solution in the healthcare field. It highlights security and privacy concerns and focuses on artificial intelligence technologies' risks and opportunities. The additional review covers how the regulatory challenges may impact the adoption of artificial intelligence in healthcare. This study further looks into the benefits and challenges of information sharing in the era of artificial intelligence. It discusses its value, technological limitations, and other key hurdles, showing how it can enhance patient experiences throughout the care process. Finally, the theoretical review of the author aims to suggest policy responses to address security, privacy, and information-sharing challenges that are being integrated by the countries in terms of artificial intelligence in their healthcare system.

3. Methodology

3.1. Material and Methods

The study framework, as seen in Figure 2, is based on past studies and finding gaps in the information management domain, knowledge sharing, and artificial intelligence. There are three main dimensions of the outcome variable: information management, online and offline knowledge sharing and artificial intelligence. The direct paths between independent and dependent variables are shown using direct arrows → while + sign reflects the hidden indicators. All variables in the study were measured through scales adapted from previous studies and validated by experts. Table 1 summarizes the statements of the consideration using the referenced studies in the questionnaire.

Table 1: Variables References and Measuring Scale.

Variables	Nature	Statements in the Questionnaire	Scale and source
Online Knowledge Sharing (OKS)	IV1	1. The advice I receive from other members through online knowledge sharing has increased my understanding of various topics. 2. The advice I receive from other members through online knowledge sharing has expanded my knowledge in different areas. 3. The advice I receive from other members through online knowledge sharing enables me to complete tasks more efficiently. 4. The advice I receive from other members through online knowledge sharing helps me improve the quality of my work. 5. The advice I receive from other members through online knowledge sharing allows me to perform tasks with greater independence.	Strongly disagree =1 and strongly agree=5
Offline Knowledge Sharing (FKS)	IV2	1. I actively share my professional knowledge `with my colleagues. 2. I voluntarily share my skills with colleagues within my department. 3. I share my work experiences and knowledge with my coworkers. 4. I try to share my expertise from education or training with other group members in a more effective way. 5. I show my co-workers how to perform the most difficult part of the work. 6. I actively answer questions posed by my coworkers	(**Khoshnaw; Karadas**, 2024)
Artificial Intelligence Familiarity (AIN)	IV3	1. I have worked with or studied Artificial Intelligence. 2. Throughout my life, I have had experience interacting with AI. 3. I am familiar with AI or AI content (texts, audiovisuals, etc.).	(**Akhtar *et al.***, 2024)
Information Management			
Information Quality (INQ)	DV1	1. The information shared between employees and the digital library is timely. 2. The information shared between employees and the digital library is accurate. 3. The information shared between employees and the digital library is complete. 4. The information shared between employees and the digital library is adequate. 5. The information shared between employees and the digital library is reliable.	(**Li; Lin**, 2006)
Information Technology (INT)	DV2	1. The digital library has direct computer-to-computer links with other internal systems. 2. Coordination within the organization is achieved using electronic links through the digital library. 3. The digital library enables information technology-supported data collection and transaction processing. 4. The digital library has electronic communication capabilities with employees for sharing information. 5. The digital library supports the electronic transfer of reports, data entries, and other relevant documents. 6. The digital library uses advanced information systems to track and manage data collection and reporting processes.	(**Prajogo; Olhager**, 2012)
Information Security INS	DV3	1. The regular information-sharing processes within the digital library have been standardized and structured to ensure the security of information flow. 2. The digital library allows the organization to clearly understand the source and use of shared information to maintain the security of the information flow. 3. The digital library ensures the security of information shared by employees and other stakeholders in the organization.	(**Qin; Fan**, 2016)

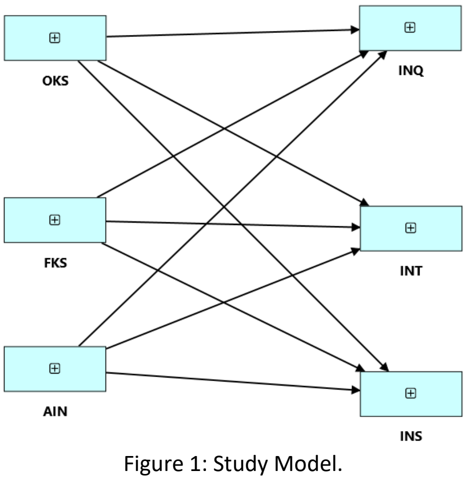

Figure 1: Study Model.

Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security; + sign reflects the hidden indicators → shows the direct path between independent and dependent variables.

3.2. Data Collection and Ethical Concerns

Once the questionnaire was adapted, the data collection procedure started. A list of available digital libraries in China was prepared, and a telephone conversation was made to ensure the availability of the relevant respondents for data collection. To ensure the respondent's confidentiality and maintain ethical standards, no question was asked during the data collection, which could lead to the identification of respondents. Therefore, the study primarily considers the privacy of the respondents.

3.3. Data Analysis Techniques

To ensure the data was analyzed using all available, relevant, and innovative techniques, the descriptive test was initially applied using the most interesting way to check the trends in the average values and standard deviation. These details are shown in Table 2, where the categories of each Mean value and Comparison/Interpretation for the standard deviation have been given. Regarding the demographic factors, the managerial position of the respondents like Digital Library Managers, IT/Technology Managers, Heads of Digital Archives/Collections, Metadata Specialists, Digital Content Managers, Digital Preservation Managers, Digital Services Librarians, Project Managers for Digital Library Initiatives, Digital Library Systems Administrators, Research Data Managers were invited using their relative gender and working experience in terms of years were asked. The next step involved testing the reliability of the items and variables with the help of factor loadings, HTMT ratio, and the Fornell-Larcker Method. The factor loading threshold level was applied as >0.70 for every item. The final stage of the data analysis determines the addressing of the research questions by using structural equation modeling. This method is not new in the literature, yet the authors have found various studies using this methodology (**Santoso; Indrajaya**, 2023; **Moscato**, 2023; **Jacqueline *et al.***, 2024).

4. Results and Analysis

4.1. Descriptive Results

The items belonging to the study's variables are presented using the descriptive results (See Table 2). A total of 310 observations shows the valid number of responses being observed for the current study. The mean values were categorized using the Likert scale as provided in the questionnaire. For example, those approaching to 4 are regarded as approaching the agreed point on the scale. In contrast, the values above 4.50 are termed as approaching to agree on the scale strongly. Additionally, standard deviation in the data covers the level of spread of the data around the mean. For example, higher standard deviation means higher spread and lower standard deviation means lower spread. Using the comparison approach, the results cover a good debate regarding the nature and trend of the deviation in the average responses provided by the study respondents. Table 2 summarizes descriptive findings, category of the mean and comparison of the standard deviations among all variables.

Table 2: Descriptive Findings, Category of the Mean and Comparison of the Standard Deviation.

Variable	Mean	Category	Std. Dev.	Comparison/Interpretation	Min	Max
OKS1	3.981	Approaching to agreed point on the scale	0.377	Low Variability: The data points are consistent and close to the mean.	2	5
OKS2	4.003	Above agreed point on the scale	0.429	Low Variability: The data points are consistent, with minimal deviation from the mean.	2	5
OKS3	4.587	Approaching to strongly agree to the scale	0.578	Moderate Variability: The data points are moderately spread around the mean.	2	5
OKS4	4.006	Above agreed point on the scale	0.41	Low Variability: The data points are consistent and closely grouped around the mean.	2	5
OKS5	3.994	Approaching to agreed point on the scale	0.441	Low Variability: The data points are closely grouped, with low variation.	2	5
FKS1	3.868	Approaching to agreed point on the scale	0.514	Moderate Variability: The data shows moderate spread from the mean.	2	5
FKS2	3.865	Approaching to agreed point on the scale	0.449	Moderate Variability: The data has moderate spread, but still within a reasonable range.	1	5
FKS3	4.632	Approaching to strongly agree to the scale	0.797	High Variability: The data points are widely dispersed, indicating high variation.	1	5
FKS4	3.916	Approaching to agreed point on the scale	0.495	Moderate Variability: The data is somewhat spread around the mean, but within a moderate range.	1	5
FKS5	3.868	Approaching to agreed point on the scale	0.568	Moderate Variability: The data shows moderate variation from the mean.	1	5
FKS6	3.913	Approaching to agreed point on the scale	0.542	Moderate Variability: The data points are spread moderately around the mean.	1	5
AIN1	3.935	Approaching to agreed point on the scale	0.524	Moderate Variability: The data has consistent spread, but not extreme.	1	5
AIN2	3.926	Approaching to agreed point on the scale	0.48	Low Variability: The data points are consistently close to the mean.	1	5
AIN3	3.913	Approaching to agreed point on the scale	0.457	Low Variability: The data is closely grouped, with low variation.	1	5
INQ1	4.703	Approaching to strongly agree to the scale	0.698	High Variability: The data shows considerable spread from the mean, indicating high variation.	1	5
INQ2	4.716	Approaching to strongly agree to the scale	0.661	High Variability: The data points have a moderate spread, indicating significant variation.	1	5
INQ3	3.894	Approaching to agreed point on the scale	0.424	Low Variability: The data is consistently around the mean, with small variation.	1	5
INQ4	3.906	Approaching to agreed point on the scale	0.477	Low Variability: The data points are consistent with small fluctuations around the mean.	1	5
INQ5	3.906	Approaching to agreed point on the scale	0.419	Low Variability: Like the previous value, the data points show minimal variation.	1	5
INT1	3.935	Approaching to agreed point on the scale	0.413	Low Variability: The data is consistent, with minimal spread around the mean.	1	5
INT2	3.797	Approaching to agreed point on the scale	0.592	Moderate Variability: The data has some fluctuation but remains relatively stable.	1	5
INT3	3.816	Approaching to agreed point on the scale	0.553	Moderate Variability: The data points are spread moderately, with some variation.	1	5
INT4	3.845	Approaching to agreed point on the scale	0.576	Moderate Variability: The data shows moderate spread around the mean.	1	5
INT5	4.69	Approaching to strongly agree to the scale	0.707	High Variability: The data points have significant spread from the mean, indicating high variation.	2	5
INT6	3.887	Approaching to agreed point on the scale	0.531	Moderate Variability: The data points show moderate variation from the mean.	1	5
INS1	4.716	Approaching to strongly agree to the scale	0.68	High Variability: The data shows considerable spread, indicating variability.	1	5
INS2	3.887	Approaching to agreed point on the scale	0.661	Moderate Variability: The data has moderate fluctuation, but still within a reasonable range.	1	5
INS3	4.706	Approaching to strongly agree to the scale	0.688	High Variability: The data points show significant fluctuation, indicating high variability.	2	5

Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security

4.2. Demographics

Figure 2 and Table 3 show the demographics of 310 respondents, holding different managerial positions in digital libraries of China. The demographics include positions, relative gender, and working experience of these respondents. The distribution shows that the highest participation came from the respondents with the position of digital library manager, 61, followed by digital service librarians, and project managers for the digital library initiatives. A total of 194 males and

116 females participated in this study. Overall, the work experience was the highest in the 0-3-year range, reflected by 134 respondents. Those covering experiences above 5 years, 114 and 62 reported their experience between 4-5 years.

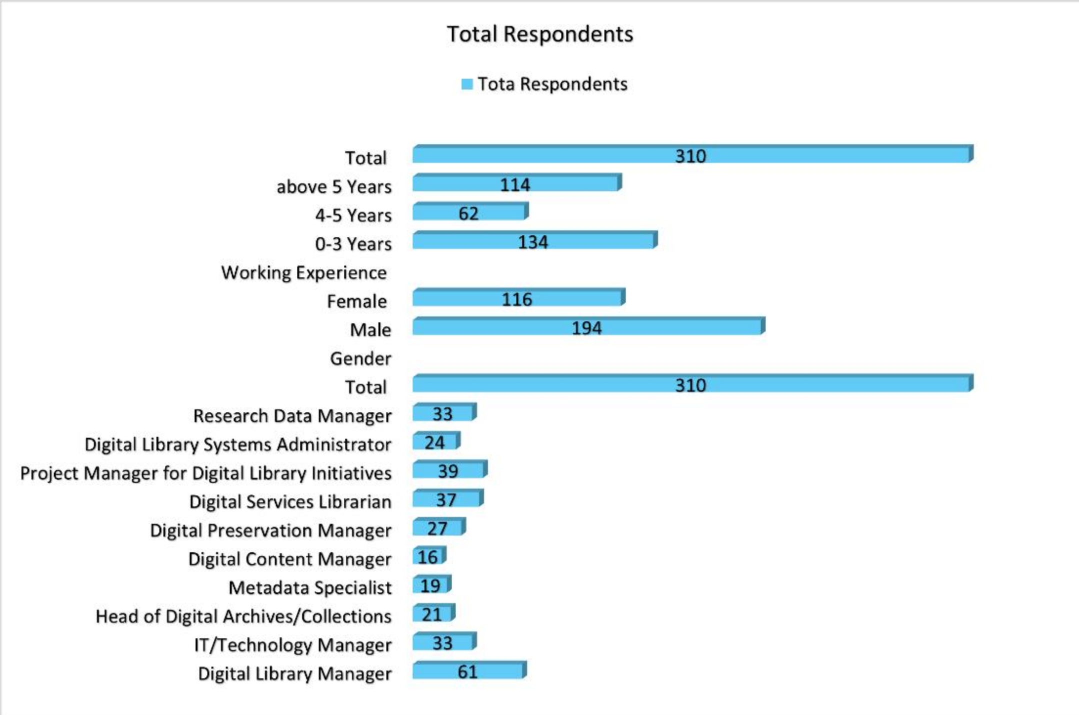

Figure 2: Demographic Factors of the Participants.

Table 3: Demographic Factors of the Participants.

Positions	Total
Digital Library Manager	61
IT/Technology Manager	33
Head of Digital Archives/Collections	21
Metadata Specialist	19
Digital Content Manager	16
Digital Preservation Manager	27
Digital Services Librarian	37
Project Manager for Digital Library Initiatives	39
Digital Library Systems Administrator	24
Research Data Manager	33
Total	310
Gender	
Male	194
Female	116
Working Experience	
0-3 Years	134
4-5 Years	62
above 5 Years	114
Total	310

4.3: Reliability of the Constructs

This model (Figure 3-a) shows the reliability results in the construction of variables OKS, FKS, INQ, INT, INS and AIN and the alpha scores using the Smart PLS 4.0 version. The results show that with the help of each variable, the alpha scores for these variables are 0.88, 0.900, 0.83, 0.86, 0.90, and 0.81 respectively. All these results are above the cut-off level of 0.70, as recommended (**Tavakol; Dennick**, 2011; **Malkewitz *et al.***, 2023; **Aburayya *et al.***, 2023), therefore, we are not in a position to infer any inference that these variables are not showing their reliability into the model, either they are dependent or independent. Figure 3-b has also been shown to display the average variance extracted and generated through the same procedure in the Smart PLS. The results of AVE reflect that for these variables, the given values are 0.69, 0.71, 0.75, 0.64, 0.68, and 0.72 respectively. These values support the presence of convergent validity, where it is recommended that the value for each of the variables must be above 0.50 (**Cheung *et al.***, 2024; **Baharum *et al.***, 2023). The reason for considering 0.50 as a threshold is that if it is lower than this level, it shows that half of the variance of the indicators is being explained by the latent variable, which is not a good indication of its presence in the model or reflecting the low level of convergent validity. We know that both the alpha and AVE values of these variables are truly above the minimum level, so we accept that not only is the reliability present in the model, but also the convergent validity exists.

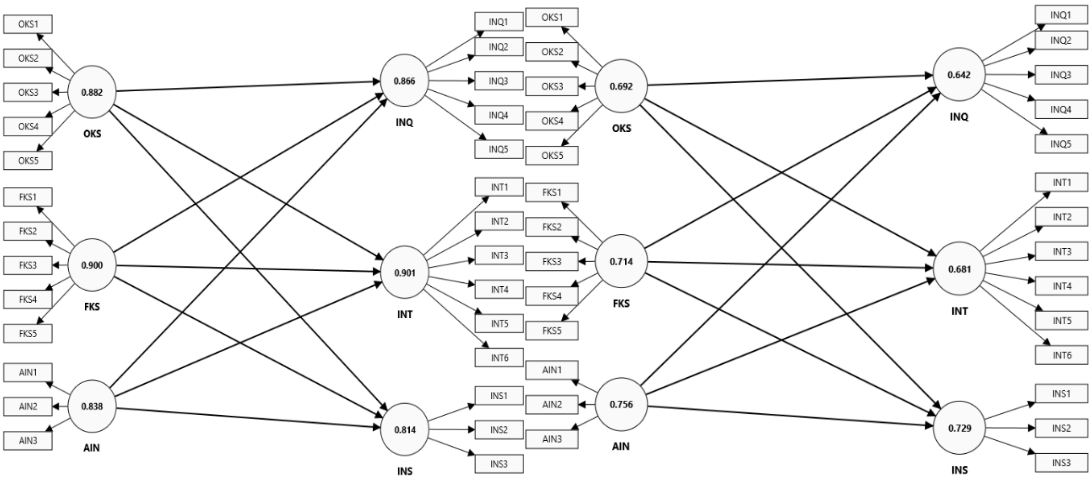

Figure 3-a and Figure 3-b: Show Alpha and AVE Values.

The findings in Table 4 check the discriminant validity using the HTMT and Fornell-Larcker methods. These two methods are mainly used for the confirmation of the discriminant validity among variables of the study (**Afthanorhan *et al.***, 2021; **Yusoff *et al.***, 2020). As per the suggested threshold points for the HTMT and Fornell Larcker, it is often suggested that the HTMT's correlation should be less than 0.85 (**Yusoff *et al.***, 2020). For the second criterion of the Fornell-Larcker, the square root of the AVE must be greater than the correlation between the two constructs (**Afthanorhan**, 2013). Both these criteria are addressed in the findings shown in Table 4. The study further clarifies the discriminant validity with the help of factor loadings. Figure 4, using the items of the variables, shows the factor loadings above 0.70.

Table 4: HTMT and Fornell-Larcker.

HTMT						
Variables	**AIN**	**FKS**	**INQ**	**INS**	**INT**	**OKS**
AIN						
FKS	0.853					
INQ	0.786	0.842				
INS	0.835	0.441	0.654			
INT	0.786	0.828	0.818	0.740		
OKS	0.677	0.623	0.672	0.528	0.635	
Fornell-Larcker						
Variables	**AIN**	**FKS**	**INQ**	**INS**	**INT**	**OKS**
AIN	0.870					
FKS	0.745	0.845				
INQ	0.709	0.807	0.802			
INS	0.708	0.825	0.830	0.854		
INT	0.707	0.763	0.898	0.891	0.825	
OKS	0.583	0.553	0.600	0.459	0.564	0.832
Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security						

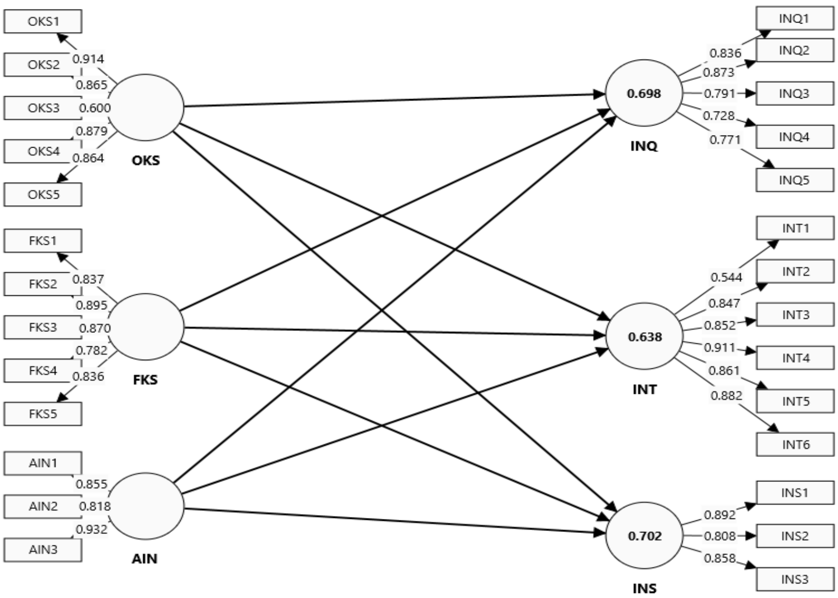

Figure 4: Factor Loadings of the Items in the Model.
Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security.

4.4. Structural Path of the Variables

The structural path aims to show the impact of online knowledge sharing, offline knowledge sharing, and artificial intelligence on information management using information quality, information technology, and information security. The structural path of variables is presented in Table 5 and Figure 5. It is revealed that (i) the impact of OKS on INQ: The path coefficient of this relationship is 0.179 when accounting for the original sample and 0.178 sample mean or M. The STDEV for this path is 0.053, and the T-statistics of this path is 3.369. The p-value of this path is 0.001. The significant p-value at 1% and good t-statistics confirm that online knowledge sharing improves information management in terms of information quality in the digital libraries of China. (ii) Impact of OKS on INS: The path coefficient of this relationship is -0.052 when accounting for the original sample and -0.047 for the sample mean or M. The STDEV for this path is 0.081, and the T-statistics of this path is 0.645. The p-value of this path is 0.519. The significant p-value is not significant at 5%, and low t-statistics confirm that online knowledge sharing has no role in improving information management in terms of information security in the digital libraries of China. (iii) Impact of OKS on INT: The path coefficient of this relationship is 0.141 when accounting for the original sample and 0.138 for the sample mean or M. The STDEV for this path is 0.052, and the T-statistics of this path is 2.75. The p-value of this path is 0.006. The significant p-value is 5%, and the provided t-statistics confirm that online knowledge sharing has a significant role in improving information management in terms of information technology in China's digital libraries.

Figure 5 also shows the path coefficients' p-values in the inner model, where the outer model is linked with the loadings and p-values.

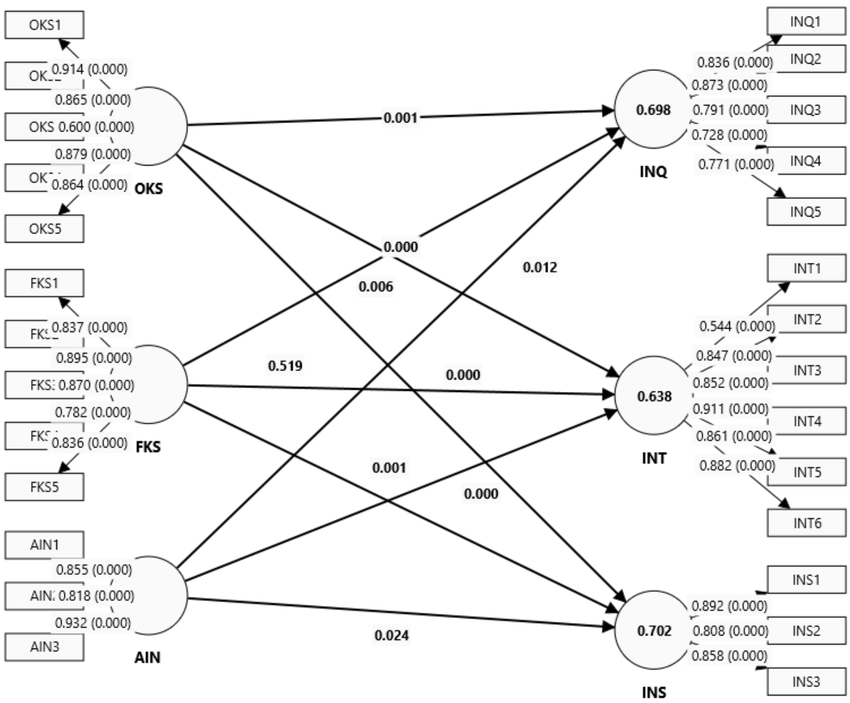

Figure 5: P-values in the Inner Model and Loadings and P-values in the Outer Model.
Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security.

(iv) Impact of FKS on INQ: The path coefficient of this relationship is 0.580 when accounting for the original sample and 0.586 for the sample mean or M. The STDEV for this path is 0.065, and the T-statistics of this path is 8.98. The p-value of this path is 0.000. The significant p-value is 5%, and provided t-statistics confirm that offline knowledge sharing has a significant role in improving information management in terms of information quality in China's digital libraries. (v) Impact of FKS on INS: The path coefficient of this relationship is 0.683 when accounting for the original sample and 0.686 for the sample mean or M. The STDEV for this path is 0.076, and the T-statistics of this path is 9.009. The p-value of this path is 0.000. The significant p-value is at 5%, and t-statistics confirm that offline knowledge sharing significantly improves information management in China's digital libraries. (vi) Impact of FKS on INT: The path coefficient of this relationship is 0.493 when accounting for the original sample and 0.494 for the sample mean or M. The STDEV for this path is 0.079, and the T-statistics of this path is 6.225. The p-value of this path is 0.000. The significant p-value is at 5%, and the provided t-statistics confirm that offline knowledge sharing has a significant role in improving information management in terms of information technology in China's digital libraries. (vii) Impact of AIN on INQ: The path coefficient of this relationship is 0.173 when accounting for the original sample and 0.170 for the sample mean or M. The STDEV for this path is 0.069, and the T-statistics of this path is 2.503. The p-value of this path is 0.012. The significant p-value is at 5%, and provided t-statistics confirm that artificial intelligence has a significant role in improving information management in terms of information quality in China's digital libraries. (viii) Impact of AIN on INS: The path coefficient of this relationship is 0.230 when accounting for the original sample and 0.226 for the sample mean or M. The STDEV for this path is 0.102, and the T-statistics of this path is 2.553. The p-value of this path is 0.024. The significant p-value is at 5%, and provided t-statistics confirm that artificial intelligence has a significant role in improving information management in terms of information security in China's digital libraries. (ix) Impact of AIN on INT: The path coefficient of this relationship is 0.258 when accounting for the original sample and 0.260 for the sample mean or M. The STDEV for this path is 0.08, and T-statistics is 3.216. The p-value of this path is 0.001. The significant p-value is at 5%, and provided t-statistics confirm that artificial intelligence has a significant role in improving information management in terms of information technology in China's digital libraries.

Table 5: Impact of OKS, FKS, and AIN on Information Management.

	Original sample (O)	Sample mean (M)	Standard deviation	T statistics	P values
OKS -> INQ	0.179***	0.178	0.053	3.369	0.001
OKS -> INS	-0.052	-0.047	0.081	0.645	0.519
OKS -> INT	0.141***	0.138	0.052	2.735	0.006
FKS -> INQ	0.580***	0.586	0.065	8.985	0.000
FKS -> INS	0.683***	0.686	0.076	9.009	0.000
FKS -> INT	0.493***	0.494	0.079	6.225	0.000
AIN -> INQ	0.173**	0.17	0.069	2.503	0.012
AIN -> INS	0.23**	0.226	0.102	2.253	0.024
AIN -> INT	0.258***	0.26	0.08	3.216	0.001
Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security					

5. Discussion

Several debatable points emerged out of the findings of this study, mainly related to the structural paths that showed the impact of online knowledge sharing, offline knowledge sharing, and artificial intelligence on information management using information quality, information technology, and information security. The first path Online Knowledge Sharing (OKS) is found improved through information quality making use of collaboration, regular updates, and input from different people linked to the digital libraries and their management. As users contribute to online platforms, they build a constantly changing collection of information that is checked, improved, and expanded over time. The additional debates state that tools like peer reviews and feedback help correct mistakes and keep the information in the digital setup of the libraries as accurate and up to date. The second path of Online Knowledge Sharing (OKS) is found improved through information security, showing many different viewpoints that makes information secure, reliable and useful in different situations, specifically in the digital environment of libraries. Both these paths confirm that Online Knowledge Sharing helps break down information silos and gives a clearer, more qualitative and secure view of the topic, leading to better information management in the organization. These two paths have indicated the impact of online knowledge sharing on the quality, security and reliability of information in China's digital libraries.

Regarding the third path of Online Knowledge Sharing and Information Technology, the positive and significant results show better information management in a similar domain. OKS is among the essential indicators for improving how information is managed in digital libraries, making it simpler to access in an organized manner. By using platforms where users can collaborate, contribute, and share knowledge in real-time, libraries can ensure their collections stay relevant. The constant flow of knowledge removes several barriers, allowing users of that information to easily access a wide range of viewpoints and the latest research. With the help of smart tools and the latest technologies, digital libraries can organize even large amounts of information efficiently and effectively. By fostering an open exchange of knowledge, these libraries enrich their content and make it much simpler for users to quickly find what they're looking for whenever they need it.

The fourth relationship covers offline knowledge sharing, which increases information management as measured through Information Quality. Offline Knowledge Sharing (FKS) enhances the quality of information in digital libraries by fostering information covering dimensions like accuracy and diversity. In face-to-face interactions among people and departmental members, individuals can clarify the details, verify the facts, and share insights. Such practices ensure that the information is reliable and comprehensive. This process also helps preserve valuable local or experiential knowledge that might not be captured in online knowledge-sharing practices. As the results suggested, the other benefits of offline knowledge sharing include improving information security and information technology. The reason is that there are several risks associated with online knowledge sharing. These risks are in the form of data breaching, hacking, and some unofficial access to the data. However, offline knowledge is often free of such risk factors where the knowledge is shared in a controlled environment. These practices ultimately improve information security, leading to secure information management results. Information management using artificial intelligence to improve the quality of such information also reflects logical phases. For example, using artificial intelligence makes it very simple for the digital libraries to categorize and manage large amounts of data and information, specifically when dealing with complex and large information. Moreover, using artificial intelligence, digital libraries can enhance information quality and decision-making capabilities.

5.1. Correlation Analysis

By the end of the results and discussion, the study further provides the debate about the correlation analysis. Table 6 and Figure 6 provide such results using Online Knowledge Sharing, Offline Knowledge Sharing, information management by Information Quality, Information Technology, Information Security, and Artificial Intelligence. As we can infer from this layout, the items listed in Table 6 report the VIF as <05, generating the statement that these items are free from the biases of the higher interdependency or multicollinearity.

Table 6: Collinearity Test Results.

Variables Items	VIF	Variables Items	VIF
AIN1	2.168	INS1	2.760
AIN2	1.772	INS2	1.438
AIN3	2.854	INS3	2.458
FKS1	2.558	INT1	1.536
FKS2	3.176	INT2	2.936
FKS3	2.617	INT3	3.149
FKS4	2.006	INT4	4.783
FKS5	2.307	INT5	2.933
INQ1	3.639	INT6	3.965
INQ2	4.234	OKS1	4.312
INQ3	2.942	OKS2	3.296
INQ4	2.609	OKS3	1.226
INQ5	2.297	OKS4	4.028
		OKS5	3.244
Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security.			

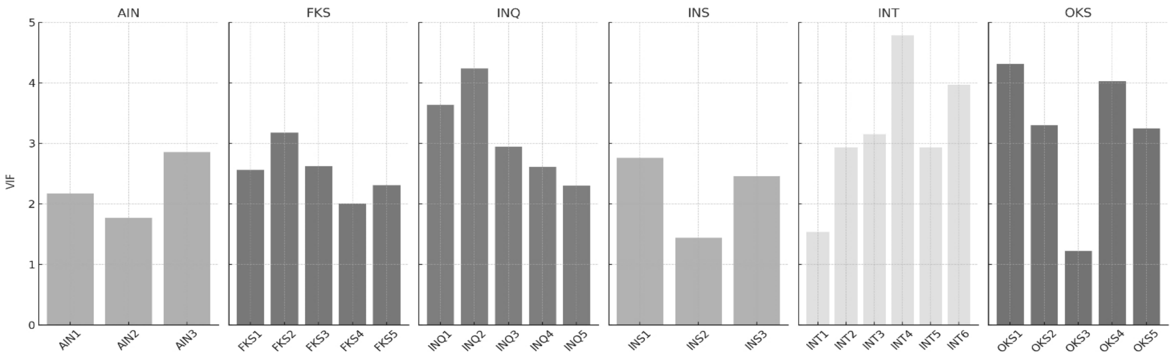

Figure 6: VIF Layout of the Variables' Items.
Note: OKS-Online Knowledge Sharing; FKS-Offline Knowledge Sharing; AIN-Artificial Intelligence; INQ-Information Quality; INT-Information Technology- INS-Information Security

6. Conclusion

Information management is a corner stone for the success of the organizations. This main idea is equally important for digital libraries, which depends on online and offline information from different resources. Simultaneously, information management using artificial intelligence improves organizational efficiency by organizing the data in a manner better than traditional data and information management strategies. This research is conducted for digital libraries in China by using both online and offline knowledge sharing and artificial intelligence as the major variables for investigating the movements in information management measured through information quality, information security, and information technology. This research investigates the role of AI in three types of information management proxies. The empirical evidence using the structural relationships evident that the collinear paths between these variables are statistically significant. The results are discussed using various other factors involved between these variables and the trends in information management.

To improve the information quality using the two of the knowledge-sharing platforms, it is mainly recommended that the online and similar other digital libraries use tools like wikis and forums to make it easier for users and experts to work in a team, considering the update to date knowledge and data using these two techniques. For this path, the technology linked with artificial intelligence can help by focusing on and addressing the errors, updating outdated information, and giving users the exact track to follow. This would improve the quality of the information by using social media platforms like WeChat. Additionally, the given productive results between knowledge sharing and quality of information are also connected with the engagement of users who are frequently linked with digital libraries. The additional possible suggestions to improve the information quality include the creation of collaborative knowledge platforms, participation from academic institutions, and customized training programs for the staff working in the digital libraries. Further suggestions cover that digital libraries in China can also avail themselves of opportunities in information management with the help of artificial intelligence. These relationships can further be improved with the help of various methodologies and long-term strategies, including strengthened cybersecurity measures. This step will improve information security and provide a safer environment for the digital transmission of information and data. Moreover, the automation of the several tasks in the digital libraries with the help of artificial intelligence will be another strategic step towards better information management practices.

This research shows certain limitations that needs attention in future studies. The first and foremost limitation is that this research examines only two key areas linked with information management: knowledge sharing and artificial intelligence. However, the missing research areas that would be of interest to future studies are information retrieval, knowledge management, data governance, information privacy, big data analytics, content management and curation, information systems design and development, cloud computing and information storage, human-computer interaction, information lifecycle management, digital libraries and archives, and so on. The second limitation is the methodological focus, where this work only talks about the quantitative investigation and completely misses the qualitative analysis. The third limitation is that it only provides evidence for different digital libraries in China and no evidence for other regional states in similar Asian regions. Future studies should take these areas and continue this journey of breaking barriers of knowledge management in digital libraries.

References

Aburayya, Ahmad; Salloum, S; Alderbashi, K; Shwedeh, Fanar; Shaalan, Yara; Alfaisal, Raghad; Malaka, S; Shaalan, Khaled. (2023). "SEM-Machine Learning-Based Model for Perusing the Adoption of Metaverse in Higher Educations in UAE". *International Journal of Data and Network Science,* v. 7, n. 2, pp. 667-676. *https://doi.org/10.5267/j.ijdns.2023.3.005*

Afthanorhan, Asyraf; Ghazali, Puspa Liza; Rashid, Norfadzilah. (2021). "Discriminant Validity: A Comparison of CBSEM and Consistent PLS using Fornell & Larcker and HTMT Approaches". *Journal of Physics: Conference Series,* v. 1874, n. 1, pp. 012085. *https://doi.org/10.1088/1742-6596/1874/1/012085*

Afthanorhan, Wan Mohamad Asyraf Bin Wan. (2013). "A Comparison Of Partial Least Square Structural Equation Modeling (PLS-SEM) and Covariance Based Structural Equation Modeling (CB-SEM) for Confirmatory Factor Analysis". *International Journal of Engineering Science and Innovative Technology,* v. 2, n. 5, pp. 198-205. *https://www.ijesit.com/Volume%202/Issue%205/IJESIT201305_27.pdf*

Akhtar, Muhammad; Salman, Asma; Abdul Ghafoor, Khalid; Kamran, Mahnoor. (2024). "Artificial Intelligence, Financial Services Knowledge, Government Support, and User Innovativeness: Exploring the Moderated-Mediated Path to Fintech Adoption". *Heliyon,* v. 10, n. 21, pp. e39521. *https://doi.org/10.1016/j.heliyon.2024.e39521*

Aslan, Mustafa. (2020). "Management Information Systems and Strategic Decision-Making." In: *Data, Information and Knowledge Management.* Mert, Gözde; Şen, Erdal; Yılmaz, Osman (Eds.), pp. 175-200. Nobel Publishing Group.

Azeroual, Otmane; Schöpfel, Joachim; Saake, Gunter. (2021). "Implementation and User Acceptance of Research Information Systems". *arXiv preprint arXiv:2111.08309*. *https://doi.org/10.48550/arXiv.2111.08309*

Baharum, Hafidza; Ismail, Aniza; Awang, Zainudin; McKenna, Lisa; Ibrahim, Roszita; Mohamed, Zainah; Hassan, Nor Haty. (2023). "The Study Adapted Instruments Based on Confirmatory Factor Analysis (CFA) to Validate Measurement Models of Latent Constructs". *International Journal of Environmental Research and Public Health,* v. 20, n. 4, pp. 2860. *https://doi.org/10.3390/ijerph20042860*

Bolisani, Ettore; Scarso, Enrico. (1999). "Information Technology Management: A Knowledge-Based Perspective". *Technovation,* v. 19, n. 4, pp. 209-217. *https://doi.org/10.1016/S0166-4972(98)00109-6*

Charband, Yeganeh; Jafari Navimipour, Nima. (2016). "Online Knowledge Sharing Mechanisms: A Systematic Review of the State of the Art Literature and Recommendations for Future Research". *Information Systems Frontiers,* v. 18, pp. 1131-1151. *https://doi.org/10.1007/s10796-016-9628-z*

Cheung, Gordon W; Cooper-Thomas, Helena D; Lau, Rebecca S; Wang, Linda C. (2024). "Reporting Reliability, Convergent and Discriminant Validity with Structural Equation Modeling: A Review and Best-Practice Recommendations". *Asia Pacific Journal of Management,* v. 41, n. 2, pp. 745-783. *https://doi.org/10.1007/s10490-023-09871-y*

Choo, Chun Wei. (2002). *Information Management for the Intelligent Organization: The Art of Scanning the Environment*. Information Today, Inc.

Dalkir, Kimiz. (2013). *Knowledge Management in Theory and Practice*. Routledge. *https://doi.org/10.4324/9780080547367*

Du Plessis, Marina. (2007). "The Role of Knowledge Management in Innovation". *Journal of Knowledge Management,* v. 11, n. 4, pp. 20-29. *https://doi.org/10.1108/13673270710762684*

Enholm, Ida Merete; Papagiannidis, Emmanouil; Mikalef, Patrick; Krogstie, John. (2022). "Artificial Intelligence and Business Value: A Literature Review". *Information Systems Frontiers,* v. 24, n. 5, pp. 1709-1734. *https://doi.org/10.1007/s10796-021-10186-w*

Franks, Patricia C. (2013). *Records and Information Management*. American Library Association. *https://alastore.ala.org/content/records-and-information-management-second-edition*

Hlávka, Jakub P. (2020). "Security, Privacy, and Information-Sharing Aspects of Healthcare Artificial Intelligence." In: *Artificial Intelligence in Healthcare.* Bohr, Adam; Memarzadeh, Kaveh (Eds.), pp. 235-270. Academic Press. *https://doi.org/10.1016/B978-0-12-818438-7.00010-1*

Jacqueline, Greisy; Senjaya, Yulia Putri Ayu; Firli, M Zaki; Yadila, Ahmad Bayu. (2024). "Application of SmartPLS in Analyzing Critical Success Factors for Implementing Knowledge Management in the Education Sector". *APTISI Transactions on Management,* v. 8, n. 1, pp. 49-57. *https://doi.org/10.33050/atm.v8i1.2201*

Khoshnaw, Doste; Karadas, Georgiana. (2024). "Transactional Leadership and Intellectual Capital, the Mediating Role of Knowledge Sharing: The Study of Customs Employees in Sulaymaniyah Governorate". *Heliyon,* v. 10, n. 19, pp. e38747. *https://doi.org/10.1016/j.heliyon.2024.e38747*

Li, Suhong; Lin, Binshan. (2006). "Accessing Information Sharing and Information Quality in Supply Chain Management". *Decision Support Systems,* v. 42, n. 3, pp. 1641-1656. *https://doi.org/10.1016/j.dss.2006.02.011*

Malkewitz, Camila Paola; Schwall, Philipp; Meesters, Christian; Hardt, Jochen. (2023). "Estimating Reliability: A Comparison of Cronbach's α, McDonald's ωt and the Greatest Lower Bound". *Social Sciences & Humanities Open,* v. 7, n. 1, pp. 100368. *https://doi.org/10.1016/j.ssaho.2022.100368*

Mikalef, Patrick; Boura, Maria; Lekakos, George; Krogstie, John. (2020). "The Role of Information Governance in Big Data Analytics Driven Innovation". *Information & Management,* v. 57, n. 7, pp. 103361. *https://doi.org/10.1016/j.im.2020.103361*

Moscato, Jason. (2023). "Evaluating Organizational Performance Using Smartpls: A Management Perspective". *APTISI Transactions on Management,* v. 7, n. 3, pp. 273-281. *https://doi.org/10.33050/atm.v7i3.2144*

Nie, Jian-Yun. (2022). *Cross-Language Information Retrieval*. Springer Nature. *https://doi.org/10.1007/978-3-031-02138-1*

Prajogo, Daniel; Olhager, Jan. (2012). "Supply Chain Integration and Performance: the Effects of Long-Term Relationships, Information Technology and Sharing, and Logistics Integration". *International Journal of Production Economics,* v. 135, n. 1, pp. 514-522. *https://doi.org/10.1016/j.ijpe.2011.09.001*

Qin, Chuanshen; Fan, Bo. (2016). "Factors That Influence Information Sharing, Collaboration, and Coordination Across Administrative Agencies at a Chinese University". *Information Systems and e-Business Management,* v. 14, pp. 637-664. *https://doi.org/10.1007/s10257-015-0298-z*

Robson, Wendy. (1997). *Strategic Management and Information Systems*. Pitman Publishing. *https://123library.org/book/266248/strategic-management-and-information-systems*

Santoso, Teguh Iman; Indrajaya, Danang. (2023). "Penggunaan SEM – PLS dan Aplikasi SmartPLS Untuk Dosen dan Mahasiswa". *Jurnal Pengabdian Masyarakat Akademisi,* v. 2, n. 2, pp. 97-104. *https://doi.org/10.54099/jpma.v2i2.630*

Tamjidyamcholo, Alireza; Bin Baba, Mohd Sapiyan; Shuib, Nor Liyana Mohd; Rohani, Vala Ali. (2014). "Evaluation Model for Knowledge Sharing in Information Security Professional Virtual Community". *Computers & Security,* v. 43, pp. 19-34. *https://doi.org/10.1016/j.cose.2014.02.010*

Tamjidyamcholo, Alireza; Bin Baba, Mohd Sapiyan; Tamjid, Hamed; Gholipour, Rahmatollah. (2013). "Information Security – Professional Perceptions of Knowledge-Sharing Intention Under Self-Efficacy, Trust, Reciprocity, and Shared-Language". *Computers & Education,* v. 68, pp. 223-232. *https://doi.org/10.1016/j.compedu.2013.05.010*

Tavakol, Mohsen; Dennick, Reg. (2011). "Making Sense of Cronbach's Alpha". *International Journal of Medical Education,* v. 2, pp. 53-55. *https://doi.org/10.5116/ijme.4dfb.8dfd*

Wang, Junkai; Wang, Aimeng; Luo, Kaikai; Nie, Yaoxiang. (2024). "Can Artificial Intelligence Improve Enterprise Environmental Performance: Evidence From China". *Journal of Environmental Management,* v. 370, pp. 123079. *https://doi.org/10.1016/j.jenvman.2024.123079*

Yadav, Alok; Garg, Rajiv Kumar; Sachdeva, Anish. (2024). "Artificial Intelligence Applications for Information Management in Sustainable Supply Chain Management: A Systematic Review and Future Research Agenda". *International Journal of Information Management Data Insights,* v. 4, n. 2, pp. 100292. *https://doi.org/10.1016/j.jjimei.2024.100292*

Yusoff, Ahmad Shidki Mat; Peng, Fan Siong; Abd Razak, Fahmi Zaidi; Mustafa, Wan Azani. (2020). "Discriminant Validity Assessment of Religious Teacher Acceptance: The Use of HTMT Criterion". *Journal of Physics: Conference Series,* v. 1529, n. 4, pp. 042045. *https://doi.org/10.1088/1742-6596/1529/4/042045*