Impact of AI-Based Learning, Digital Literacy, Information Stewardship on Learning Outcomes

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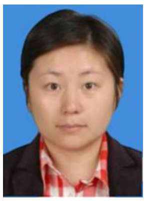

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Abstract

Rapid technological advancement has given rise to AI-based learning which necessitates managing and protecting the information within organizations. This highlights the accountability of factors like digital literacy and information stewardship on achieving the learning outcomes. This study aims to conduct a quantitative investigation of the impact of AI-based learning, digital literacy, and information stewardship on the learning outcomes among employees in the research and development departments of information technology firms in China. Three measures were considered to reflect AI-based learning: effective learning, problem-solving, and learning exposure. The study developed a structural questionnaire for measuring the given variables using an in-depth review of past studies. The final sample comprised 255 respondents from several IT firms with research and development departments in China. The study explored the respondents by using their distribution by gender, age, working experience, and interest in information technologies. The subsequent measurement model analysis validated the questionnaire and items of the variables through reliability and discriminant validity. The results using the structural equation modeling technique confirm that artificial intelligence learning exposure and effective learning are positively connected to learning outcomes among the employees of R&D departments of IT-based firms. Moreover, information stewardship confirms that a higher level of such stewardship means higher learning outcomes among similar employees of the targeted industry. The study findings would be of great support to policymakers who are involved in information and data management and learning through AI-based models. The policy implications also provide suggestions for future studies as observed through key limitations.

Keywords

Information Stewardship, AI-based Learning, Digital Literacy, Learning Exposure, Learning Outcomes, IT Firms.

1. Introduction

One of the general concepts of Information Stewardship (IFS) reveals that it is related to managing and protecting the information within the organization's context in a responsible way. It focuses on keeping information more accurate, secure, accessible, and private at every stage of its usage within the organization. This idea highlights the need for accountability and ethical practices when handling data and related material, especially when dealing with sensitive or restricted information of the organization. In this regard, the research (**Smallwood**, 2019) explained that information governance frameworks can create clear rules for handling data responsibly while helping organizations follow the stated ethical standards. He further points out that information stewardship requires integration from several departments to manage data on proper grounds. Therefore, the stated organizational policies and standards play an important role in keeping data accurate and secure while reducing the chances of data being misused or exposed in a breach (**Smallwood**, 2019). The recent literature evidence favors using advanced technologies for the transformative learning experience (**Ali**, 2023; **Demir *et al.***, 2024). In this regard, the AI-based tool like ChatGPT provides a good example of the usage of advanced technology which has reshaped the learning experience in different fields of life (**Dalgıç *et al.***, 2024; **Prananta *et al.***, 2023; **Beerbaum**, 2023).

While digitalization and technological advancements have brought various new opportunities, they also come with certain challenges. For instance, more research is needed to understand how AI-related technologies, digital literacy, and personalized learning will impact learning outcomes. As noted by recent studies conducted by **Dwivedi *et al.*** (2023) and **Gursoy *et al.*** (2023), one of the most discussed topics recently is AI-based tools like ChatGPT. **Gupta *et al.*** (2023) have further suggested that the progress in information processing technologies will speed up the adoption of artificial intelligence, helping people meet personal and professional needs. Moreover, the concept of AI has also been utilized in terms of its effectiveness. For example, **Baillifard *et al.*** (2024) have considered the nexus between effective learning by using the AI as a personal tutor. The results confirm that students who use AI as a personal tutor are gaining higher grades, leading to an effective way of learning. However, under which direction the relationship between effective learning and learning outcomes are connected for the employees working in the information technology firms and their research and development departments is still a major gap in the literature to date. Moreover, like other benefits, AI learning can be reflected by exploring its role as a problem solver (**Raisch; Fomina**, 2023). Organizations are widely using AI-based technology to solve different types of complex problems. Although the routine task is automated, the nature of the exploration tasks, such as new problems, demands a high level of integration between human intelligence and artificial intelligence (**Raisch; Fomina**, 2023). For this reason, researchers in the available studies put their reasonable efforts into articulating the problem-solving role of artificial intelligence and learning outcomes (**Ouyang *et al.***, 2023; **Wichert**, 2020).

Digital literacy (DIG) has been recognized as the skill to use and work with digital technology, whereas artificial intelligence is the ability to apply smart algorithms to process information. Both these concepts are now essential in today's changing market environment. For instance, artificial intelligence can track the performance of employees and other individuals working in diversified organizations in real time, helping the management to look at the performance of the relevant individuals and the departments as a whole (**Okunlaya *et al.***, 2022). The growth of e-learning applications as flexible and interactive tools that can be used anytime and anywhere is also remarkable (**Schulz**, 2023). This is particularly important for regional languages, as it supports preserving and enhancing language skills that often face challenges in a globalized world (**Malik *et al.***, 2018). DIG is more than just using technology due to several basic reasons. For example, DIG involves understanding, analyzing, and creating digital content as available over the web (**Reddy *et al.***, 2022). Even though Generation Z has grown up with digital tech, they still need structured guidance to fully develop digital literacy skills (**Chan; Lee**, 2023). At the same time, in education, digital literacy is essential for helping students analyze information and present data effectively (**Kure *et al.***, 2023). This given concept of DIG is equally important in fields like accounting, where understanding digital tools is key to managing complex data (**O'Callaghan *et al.***, 2021). In the modern changing market conditions, DIG includes research, analysis, and effective digital communication, as expressed by **Reddy *et al.*** (2022). However, whether digital literacy in the organizational work setting has the potential to determine the learning outcomes of the employees is not fully examined specifically in a quantitative manner.

2. Review of Past Studies

A conclusive summary of past studies covering AI-based learning, digital literacy, information stewardship, and learning outcomes is presented in Table 1.

Figure 1 shows the framework of the study.

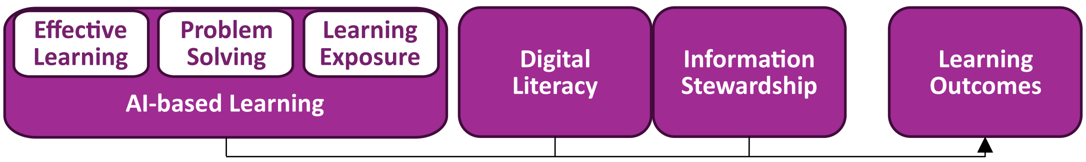

Figure 1: Research Framework.

Table 1: Conclusive Summary of Past Studies.

Study Source	Variables	Methodology	Results	Regional/Other Implications
(Yue Yim, 2024)	AI literacy, educational level, Bloom's taxonomy, constructionism, computational thinking, AI ethics	Scoping review of 19 articles across four credible index databases	Identified 17 AI literacy frameworks; highlighted that AI literacy is at the intersection of digital literacy, data literacy, computational thinking, and ethics, with a need for a transdisciplinary approach.	Emphasizes developing primary-level AI literacy frameworks globally, addressing gaps in early AI education.
(Chen *et al.*, 2024)	AI self-efficacy, AI-related anxiety, attitude toward AI, Technology Acceptance Model (TAM)	Structural equation modeling (SEM) with data from 429 Chinese L2 learners using online surveys and established TAM scales	AI self-efficacy positively affects attitudes and reduces anxiety, which influences AI tool usage; anxiety negatively impacts AI tool usage.	Insights for incorporating AI in language learning in higher education, especially in Asian regions.
(Zhang *et al.*, 2024)	Perceived ease of use (PEU), perceived usefulness (PU), attitude (A), intentions (I), concentration (C)	Linear mixed models and path analysis on the impact of AI-generated short videos vs. paper-based materials on learning	AI-generated videos enhance learning outcomes for lower-pre-test students with high PEU, PU, A, I, and C; paper materials suit higher-pre-test students with low levels in these factors.	Provides guidance for material selection in language learning for varied student proficiency levels.
(Dalgıç *et al.*, 2024)	ChatGPT, digital literacy, individualized learning, learning outcomes	Experimental use of ChatGPT, followed by online surveys among tourism students	ChatGPT improves learning outcomes, with digital literacy as a mediator and individualized learning as a moderator, suggesting a positive impact on personalized learning and skill development in tourism education.	Highlights the potential role of ChatGPT in tourism education and the importance of digital literacy globally.
(Zheng *et al.*, 2024)	Digital etiquette, digital citizenship, digital game-based learning (DGBL), student engagement, motivation	Quasi-experiment with DGBL on primary students in Guangzhou, China, to foster digital etiquette	DGBL improves digital etiquette literacy, student motivation, and engagement compared to conventional learning methods.	Supports the integration of digital citizenship and etiquette education in primary schools worldwide.
(Imjai *et al.*, 2024)	Logical Thinking Skills, Digital Literacy, Self-Learning Capability, internship performance	Quantitative research using PLS-SEM on data from 559 Thai Gen Z accounting students through online surveys	Logical Thinking Skills and Digital Literacy significantly influence internship performance; high Self-Learning Capability enables students to apply these skills effectively, incorporating online resources for self-development, enhancing career readiness.	Emphasizes the need for Thai accounting programs to integrate these skills in curricula to prepare students for the profess
(Detlor *et al.*, 2011)	Student demographics, learning environment factors, information literacy program components	Interviews with library administrators, librarians, faculty, and students across three business schools	Developed a new theoretical model identifying factors influencing student learning outcomes in information literacy instruction (ILI), including environment and demographic variables.	Suggests ways for business schools to enhance ILI programs for improved student outcomes.
(Senkbeil, 2023)	ICT literacy, parental ICT values, monitoring/supervision, ICT self-efficacy	Objective testing of ICT literacy with data from 422 children and their parents, including adolescent and parent perspectives	Parental ICT values positively predict ICT literacy, while monitoring negatively predicts it. Adolescent reports predict ICT self-efficacy better, whereas parent reports predict ICT literacy more effectively.	Highlights the importance of parental attitudes in influencing children's ICT literacy and self-efficacy.
(Chen *et al.*, 2023)	Self-regulated learning (SRL), affective learning, teacher support, digital reading performance	Multilevel latent profile analysis (LPA) with data from 34,000 students across Asian and Western educational systems	Self-regulated learning is a key factor in digital reading performance; teacher support predicts SRL but not affective learning. Cultural variations exist in SRL and affective learning patterns across Eastern and Western systems.	Emphasizes the role of cultural factors in SRL and digital reading across regions.
(Zhao *et al.*, 2024)	Cultural and creative industries (CCI), sustainability, deep learning, information management, urban development	Factor analysis and LSTM-based recommendation model for CCI development in six Chinese cities	Developed a CCI recommendation model with 94.74% accuracy, highlighting factors such as asset investment and cultural financing as critical for sustainable CCI development.	Offers insights into urban CCI development with a focus on sustainability in the Chinese context.
(Robichaud *et al.*, 2024)	Parental apologies, adolescent information management strategies (disclosure, lying, secrecy), adolescent adjustment	Correlational and experimental study on parental apologies and adolescent information management strategies	Parental apologies with need-supportive elements positively affect adolescent disclosure; need-thwarting apologies are linked with lying and secrecy.	Provides guidance for enhancing adolescent-parent communication for positive adjustment across family cont

3. Research Methods and Techniques

Table 2: Variables and their Measurement Items.

Variable	Nature	Measurement
AI-based Learning		
– Effective Learning	DV	1. Easy usage 2. Suitable results for learning 3. Saving time 4. Up-to-date information 5. Easy access to resources Accurate information
– Problem-solving	DV	1. Provide solutions to complex problems. 2. Results through data and analysis 3. Produce results and data patterns 4. Predict future outcomes
– AI learning exposure	DV	1. Improve learning experience through individual characteristics 2. providing instant feedback 3. Increase learning through content customization
Digital literacy	DV	1. Using digital tools for new learning 2. Searching information through AI-based application 3. Identification of scams and malicious using AI.
Learning outcomes	DV	1. Attain targeted information using AI. 2. Satisfactory contents 3. Improved critical thinking skills 4. Improving self-learning skills.
Information stewardship	IV	1. The organization understands and communicates well its responsibility in handling sensitive data 2. The organization complies with relevant data protection regulations. 3. The data management practices are transparent.

This research covers primary and secondary data based on which a questionnaire was constructed to measure the given variables. Each variable was examined for various factors that contributed to its understanding in the context of learning about IT organizations. For example, AI-based learning variable covered three factors: effective learning, problem-solving, and learning exposure. These factors were measured through six, four, and three items, respectively. Similarly, digital literacy was measured through three items, namely using digital tools for new learning, searching information through AI-based application, and Identification of scams and malicious using AI. Likewise, the dependent variable of learning outcomes covered four items, and the independent variable information stewardship was measured through three items. Table 2 presents these variables and their measurement items.

These items were measured using the strongly disagree as 1 and strongly agree as 5 on a Likert scale. The questionnaire was distributed among information technology firms and their research and development departments. A total of 300 questionnaires were distributed over five weeks. However, in return, the researchers collected 278 questionnaires. Moreover, further investigation showed that 23 questionnaires were dropped due to invalid responses, reaching a final sample of 255 as analyzed using the given techniques. It is important to note that the current literature also justifies the usage of the demographic factors to describe the respondents' profile. The demographic factors included gender, age, working experience, and interest in the technology, as shown in the next section of the study. The study results section is based on the methods laid out in Figure 2.

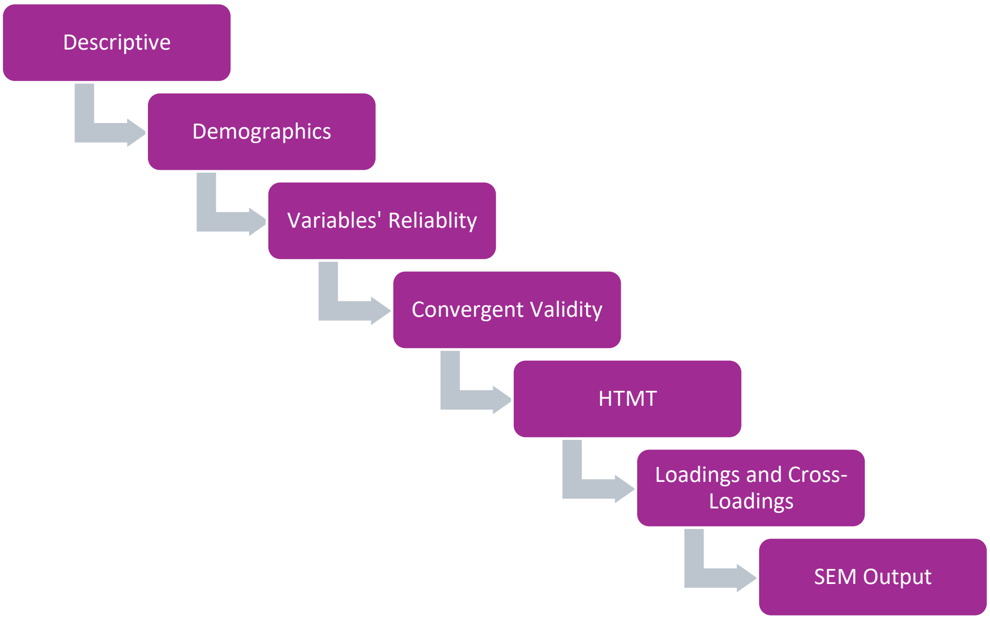

Figure 2: Methodological Sequence.

In the first step of the analysis, we applied the descriptive results covering the Mean and standard deviation as key output. In the next step, the demographic analysis using the frequency distribution and percentage share was calculated and tabulated. Next, the reliability and validity of the model with the help of measurement model implications were measured. The next step focused on the HTMT ratio and the loadings and cross-loadings, which are among the integral components of the testing for discriminant validity. Discriminant validity measures whether the model's items show a relative variance. The last empirical part encompassed the structural model output. The SEM path analysis helps answer whether significant relationships exist between the explanatory and the dependent variables in the same model. The testing of the relationships chiefly depends upon the significance level, which is considered 5%, and the t-value, respectively. To accept the significant relationships between the variables, it is important to explore the coefficients' direction and the significance level and t-value. In this research, the findings for the structural model are well presented by providing enough discussion exploring the impact of the independent variables on the learning outcomes.

4. Results

Before covering the empirical findings regarding the impact of effective learning, problem-solving, AI learning exposure, digital literacy and information stewardship on the learning outcomes, this research reflects upon the key statements for discussing the Mean, median, scale minimum-maximum, observed minimum-maximum and standard deviation in the last column. Table 3 shows good diversification, which means that the trend in the data is not similar for the given items, rather than changing according to the given responses. The maximum mean score is 4.778 as reflected by the DIG2, and 4.76 as shown by DIG3. However, the lowest average score is linked with the IFS1, which is 3.824. The overall mean values are above 3 and approaching 4, meaning that the responses are near the fourth point on the Likert scale which is 4. The consideration of the standard deviation shows that PRS2 has the highest deviation in the Mean whereas EFL1 has the lowest such deviation. However, all the deviation values are less than one.

Table 3: Descriptive Results.

Statements	Variable	Mean	SD	Min	Max
Improve learning experience through individual characteristics	AIL1	3.959	0.497	1	5
providing instant feedback	AIL2	3.952	0.453	1	5
Increase learning through content customization	AIL3	3.969	0.447	1	5
Using digital tools for new learning	DIG1	3.935	0.397	1	5
Searching information through AI based application	DIG2	4.778	0.617	1	5
Identification of scams and malicious using AI.	DIG3	4.764	0.596	1	5
Easy usage	EFL1	3.986	0.326	2	5
Suitable results for learning	EFL2	4.027	0.401	2	5
Saving time	EFL3	4.692	0.531	2	5
Up-to-date information	EFL4	4.005	0.354	2	5
Easy access to resources	EFL5	3.995	0.381	2	5
Accurate information	EFL6	3.925	0.478	2	5
The organization clearly understands and communicates its responsibility in handling sensitive data	IFS1	3.824	0.534	1	5
The organization complies with relevant data protection regulations.	IFS2	3.839	0.502	1	5
The data management practices are transparent	IFS3	3.86	0.52	1	5
Attain targeted information using AI	LOU1	3.896	0.395	1	5
Satisfactory contents	LOU2	3.906	0.438	1	5
Improved critical thinking skills	LOU3	3.906	0.391	1	5
Improving self-learning skills.	LOUT4	3.928	0.386	1	5
Provide solution to complex problems.	PRS1	3.899	0.392	1	5
Results through data and analysis	PRS2	4.725	0.707	1	5
Produce results and data patterns	PRS3	3.961	0.459	1	5
Predict future outcomes	PRS4	3.901	0.494	1	5
Note: EFL; Effective Learning, PRS; Problem Solving, AIL; Artificial Learning Exposure, DIG; Digital Literacy, LOU; Learning Outcomes, IFS; Information Stewardship.					

The respondent profile encompasses their gender, age, group, working experience, interest in the technology and employment status. The distribution of the frequency highlights that 65% are males whereas 35% are females. The other side in terms of age show that out of total sample of 255, 41.96% are in the age category of between 26.-35 years, showing the highest share in the respondents. The other results show that for the age group of above 55 years, there were only 21 respondents. For the working experience, 53% respondents had a relative experience of 0-3 years. Conversely, 23.92% confirm that their experience-wise background is 4-6 years.

Additionally, the other experience groups like 7-10 years confirmed the responses from 32 respondents and those having above 10 years were 25 respondents who participated in this study. The overall distribution for the interest in technology shows that 191 participants were technology enthusiasts, whereas the rest were average users of it. The employment status reflected that 207 respondents held permanent job and the remaining were on contracts. Table 4 and Figure 3 present the distribution of respondents using Gender, Age, Working Experience, Interest in Technology, and Employment Status both via frequency distribution and by the percentage share.

Table 4: Respondent Distribution Via Gender, Age, Working Experience, Interest in Technology, and Employment Status (n=255).

Description	Frequency	Percentage
Gender		
Male	167	65.49
Female	88	34.51
Age Group		
18-25 Years	69	27.06
26-35 Years	107	41.96
36-45 Years	35	13.73
45-55 Years	23	9.02
Above 55 Years	21	8.24
Working Experience		
0- 3Years	137	53.73
4-6 Years	61	23.92
7-10 Years	32	12.55
above 10 Years	25	9.80
Interest in Technology		
Enthusiast	191	74.90
Average User	64	25.10
Employment Status		
Permanent	207	81.18
Contractual	48	18.82

Figure 3: Demographic Variables, Frequency and Percentages.

The model reliability for the variables AIL, DIG, EFL, IFS, LOU, and PRS are well covered in Table 5, focusing on the Cronbach alpha Composite reliability (rho_a) and Composite reliability (rho_c). For example, the Cronbach's alpha for the variables is 0.827, 0.875, 0.867, 0.903, 0.901, and 0.875. These values are as per the suggestions in the literature are above 0.70 to confirm the model's reliability. For the composite reliability, the results are also shown that all the variables have a score of above 0.70. More specifically, al variables AIL, DIG, EFL, IFS, LOU, and PRS have their rho_and rho_c values equal to 0.921, 0.902, 0.935, 0.905, 0.906, 0.923, and 0.888, 0.923, 0.9, 0.94, 0.931, and 0.91 respectively as shown in Table 5. The presented scores are a good indication of model's reliability, meaning that all of the variables of this study are valid and have no issue in terms of reliability when measured through different items from the existing body of literature.

Table 5: Variables' Reliability.

Description of the Measures	AIL	DIG	EFL	IFS	LOU	PRS
Cronbach's alpha	0.827	0.875	0.867	0.903	0.901	0.875
Composite reliability (rho_a)	0.921	0.902	0.935	0.905	0.906	0.923
Composite reliability (rho_c)	0.888	0.923	0.9	0.94	0.931	0.91
Note: EFL; Effective Learning, PRS; Problem-Solving, AIL; Artificial Learning Exposure, DIG; Digital Literacy, LOU; Learning Outcomes, IFS; Information Stewardship.						

The convergent validity aims to reflect the amount of the variance being captured by the latent variable compared to the variance due to the measurement model. The average variance extracted formula is where the sum of the Squared Loadings of Indicators is divided by the number of indicators captured into the model stated in equation 1.

AVE=∑ (Squared Loadings of Indicators) / Number of Indicators *Equation 1*

Using this equation, Table 6 depicts the AVE value for AIL as 0.725 and for DIG and EFL as 0.80 and 0.060. Moreover, other variables, IFS, LOU, and PRS, have their AVE values of 0.838, 0.771, and 0.718, respectively. The recommended threshold level of AVE value is above 0.50 for variables into the model (**Afthanorhan**, 2013; **Tarmizi *et al.***, 2023). Hence, we have achieved that AVE for the variables.

Table 6: Convergent Validity.

Variables	Average variance extracted (AVE)
AIL	0.725
DIG	0.800
EFL	0.609
IFS	0.838
LOU	0.771
PRS	0.718

Discriminant validity was also measured using the methodological output in terms of HTMT ratio. The HTMT ratio threshold is <0.85 (**Ab Hamid *et al.***, 2017; **Henseler *et al.***, 2015). The results are shown in Table 7 as diagonal and off-diagonal values. For example, for the diagonal values, the correlation between AIL and DIG, between DIG and FEL, between EFL and IFS, between IFS and LOU, and between LOU and PRS were measured as 0.893, 0.715, 0.524, 0.726, and 0.506 respectively. These values were calculated using the following Equation 2:

HTMT_ij = Average of Heterotrait-Heteromethod correlations (between constructs i and j) / Average of Monotrait-Heteromethod correlations (within constructs i and j) Equation 2

Table 7: HTMT.

Variables	AIL	DIG	EFL	IFS	LOU	PRS
AIL						
DIG	0.893					
EFL	0.808	0.715				
IFS	0.650	0.890	0.524			
LOU	0.302	0.610	0.510	0.726		
PRS	0.863	0.777	0.737	0.732	0.506	

The loadings and the cross-loadings of all variables and their respective items were also measured to confirm the presence of discriminant validity. The results in Table 8 present the multiple outcomes. The bold values show the loadings for all the items of variables as selected, whereas the normal values are off-loadings. For the items of the variables, the provided loadings are well above the cross-loadings. This trend provides good justification for the existence of discriminant validity in this research's model.

Table 8: Loadings and Item's Loadings.

Items	AIL	DIG	EFL	IFS	LOU	PRS
AIL1	**0.865**	0.643	0.643	0.476	0.200	0.623
AIL2	**0.868**	0.674	0.346	0.591	0.318	0.606
AIL3	**0.820**	0.620	0.656	0.387	0.156	0.603
DIG1	0.812	**0.851**	0.553	0.640	0.475	0.702
DIG2	0.645	**0.895**	0.555	0.678	0.412	0.846
DIG3	0.605	**0.936**	0.470	0.809	0.578	0.809
EFL1	0.533	0.479	**0.911**	0.401	0.538	0.469
EFL2	0.561	0.327	**0.820**	0.156	0.180	0.453
EFL3	0.450	0.268	**0.548**	0.449	0.290	0.535
EFL4	0.407	0.420	**0.886**	0.372	0.427	0.385
EFL5	0.429	0.437	**0.885**	0.355	0.479	0.355
EFL6	0.468	0.321	**0.533**	0.427	0.188	0.447
IFS1	0.534	0.718	0.440	**0.908**	0.580	0.597
IFS2	0.502	0.710	0.334	**0.930**	0.614	0.641
IFS3	0.596	0.766	0.492	**0.908**	0.627	0.685
LOU1	0.379	0.571	0.368	0.733	**0.873**	0.469
LOU2	0.192	0.463	0.410	0.519	**0.889**	0.388
LOU3	0.288	0.516	0.511	0.627	**0.909**	0.462
LOUT4	0.125	0.383	0.474	0.424	**0.839**	0.410
PRS1	0.516	0.738	0.515	0.616	0.516	**0.916**
PRS2	0.617	0.845	0.435	0.692	0.438	**0.871**
PRS3	0.612	0.528	0.475	0.268	0.165	**0.736**
PRS4	0.750	0.786	0.531	0.646	0.417	**0.857**

Note: EFL; Effective Learning, PRS; Problem Solving, AIL; Artificial Learning Exposure, DIG; Digital Literacy, LOU; Learning Exposure, IFS; Information Stewardship.

Figure 4 presents items' loadings for IFS, EFL, PRS, LOU, AIL and DIG. As per the similar results in Table 8, the Figure 3 also confirms that the loadings are acceptable for the given variables, as they helped to provide good reliability and validity scores. The inner path of the model in Figure 4 covers the correlation between the variables where the relationship between IFS and LOU is 0.663, between DIG and LOU is 0.555, between EFL and LOU is 0.502, between PRS and LOU is 0.495, between AIL and LOU is 0.287, accordingly.

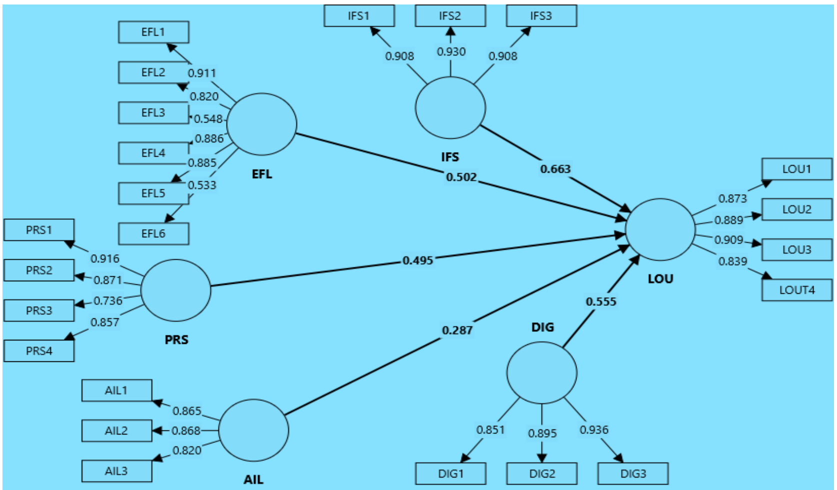

Figure 4: Correlation and Factor Loadings.

Note: EFL; Effective Learning, PRS; Problem Solving, AIL; Artificial Learning Exposure, DIG; Digital Literacy, LOU; Learning Exposure, IFS; Information Stewardship.

The structural equation modeling results are reflected in Table 9, showing different direct path analysis. The given paths in the first column determine the impact of the given independent variables on the learning outcomes, which are the main dependent variables. As the results show, the AIL to LOU coefficient is 0.438 and the standard deviation is 0.184. The given positive coefficient of 0.438, which determines an upward change in the learning outcomes also reflected by significant p-value as 0.018 at 5%. This overall trend shows that a good change in the learning outcome is connected with the learning exposure from artificial intelligence.

Table 9: Structural Equation Modelling Results.

	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
AIL -> LOU	0.438	0.184	2.375	0.018
DIG -> LOU	0.173	0.277	0.625	0.532
EFL -> LOU	0.370	0.111	3.347	0.001
IFS -> LOU	0.595	0.150	3.979	0.000
PRS -> LOU	0.028	0.181	0.152	0.879
Note: EFL; Effective Learning, PRS; Problem Solving, AIL; Artificial Learning Exposure, DIG; Digital Literacy, LOU; Learning Exposure, IFS; Information Stewardship.				

The given coefficient 0.370 of EFL to LOU implies that it is causing an improvement in the learning exposure of the targeted respondents by 0.370 while keeping the other factors as constant. Moreover, the deviation from this given coefficient has been found as 0.111 with a t-score of 3.347 which is reasonably above the level of 1.96. These results provide the stated evidence for the significant impact of the EFL on the LOU among the key officers working in the research and development department of the information technology firms. The given effect is significant, which means there is enough statistical evidence to claim that a higher level of the EFL means higher learning exposure among these respondents, for which several policy implications can be suggested. These results also claim that EFL is essential and crucial for building people's skills as they work and are linked with the Research and Development units of the information technology organization. When companies create a culture of continuous learning within the organization, the employees can stay up to date with rapid technology and the changes and tackle complex business and market-related challenges more effectively. By participating in different training sessions, using relevant resources, and collaborating with experts both within and outside the organization, the R&D staff can enhance their problem-solving skills and learn new ways of dealing with the complex business environment in a more effective manner (**Frank *et al.***, 2020; **Şenocak; Demirkıran**, 2023).

The organizational significance of information stewardship towards promoting learning and improving the performance cannot be neglected. Given this relationship, the findings in the Table 9 also show that the coefficient for the impact of information stewardship on the learning exposure is 0.595, significant on statistical grounds, and reflecting that it is putting an upward impact on the learning factor. Hence, their relationship also aims to cover some policies related to future recommendations and implications. However, the last part between problem-solving and learning exposure is insignificant, as per the given results and p-values. This suggests that there is no consideration of such a relationship while providing the policy implications and recommendations. The relationship between LOU and given variables is well covered in Figure 5, covering the p-values both in the inner and outer model as linked with the items of the variables.

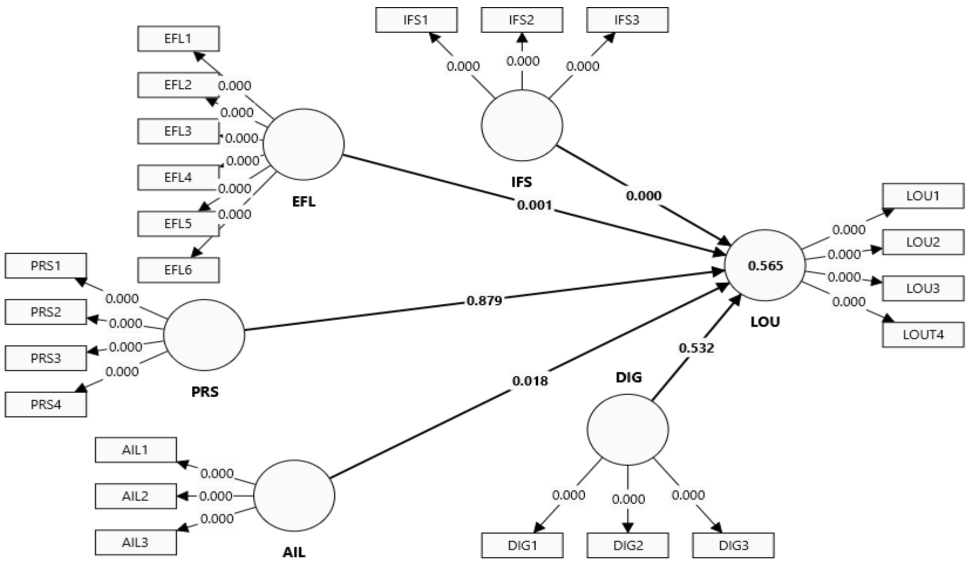

Figure 5: With p-values Inside and Outside.

More specifically, the given positive coefficient means that improvement in the learning exposure is connected with the

IFS among the information technology firms' research and development department's employees. This impact is also found as significant at 1% as all T-values are above the defined level of 1.96 and the p-value is less than zero percent. The given values like the T and the P confirm that this research study accepts the significant and productive influence from the IFS towards improving learning exposure.

This relationship involves several other factors that are quite evident to explore. The given factors can be explained in several contexts like IFS improves employee learning in the R&D departments of IT firms by organizing and managing data. The data management includes the steps like easy access, usage, and share with the other team members of the organization specifically those working in similar research and development departments. Moreover, when both the data and resources are stored in an organized and secure manner, the employees working in the R&D department can quickly find the information they need. This can lead towards time saving and help them to learn more efficiently. For instance, having well-organized databases, clear documentation, and accessible knowledge-sharing platforms allows employees to learn from past projects, avoid repeated mistakes, and build on previous successes (**Singh**, 2024). This access to structured information helps them apply insights from past work to new challenges, supporting their growth and problem-solving abilities.

The variable of information stewardship also encourages the responsible use of data (**Rosenbaum**, 2010), which is crucial in R&D as employees experiment and innovate. When data is handled properly, it is accurate and reliable, so employees can trust it and make better decisions. This trust makes them more willing to explore new ideas and collaborate with others since they know the information they're using is dependable. As a result, information becomes a valuable shared resource that everyone in the R&D department can learn from and build upon. This access to reliable information improves individual learning and boosts teamwork and innovation by creating a solid foundation of knowledge for employees to use in their projects.

The existing literature has also explored the association between the artificial intelligence learning exposure and learning outcomes. Among the sample studies, **Goksel Canbek and Mutlu** (2016) indicate that in the modern technology-based environment, it is possible to access the useful and timely information with the help of intelligent personal assistance. Meanwhile, the artificial intelligence can help in learning better by changing lessons to match each person's strengths, weaknesses, and learning style as well. Moreover, it further aims to adjust the content based on how a student is doing, making it easier for them to learn and giving extra help if they're finding something hard. Students also get quick feedback on exercises, so they can see mistakes and fix them right away. AI-powered tools are available all the time, so the individuals working at different organizations can get help whenever they need it, even if they do not have someone to guide them. Teachers also benefit because AI reveals to them each student's progress, helping them change their teaching to fit each student's needs. AI adds game-like rewards and badges, to keep students interested, which makes learning more fun.

Meanwhile, AI also groups students with similar needs together for teamwork, which builds communication and social skills. It helps students with disabilities or language differences by offering tools like voice typing or translations. With AI learning apps, students can also study anytime they want, which lets them go over and strengthen what they have learned at their own pace. All these features make learning more enjoyable and give students the support they need to succeed in ways that feel right for them. Therefore, AI is believed to boost the learning exposure of different individuals with some remarkable outcomes. However, unlike the positively significant impact of the artificial intelligence learning on the learning exposure, the impact of the digital literacy on the LOU was found to be positive but statistically insignificant when checked through full sample analysis with the help of structural equation modelling technique.

Additionally, the learning programs offered by organizations would help them stay connected with the industry trends, tools, and frameworks (**Giannakos *et al.***, 2022) that are crucial in the field of information technology research. This commitment and dedication towards the learning supports personal growth, boosts job satisfaction, and builds a strong knowledge foundation among the team members and the organization. This means employees are better prepared to think creatively, explore new ideas, and help their company stay competitive in an ever-changing industry. Additionally, a strong and committed learning environment encourages team members to acquire, share and respond for better knowledge management practices (**April *et al.***, 2004). Meanwhile learning initiatives like workshops, seminars, and online courses encourage collaboration and bring in new ideas that improve team performance (**Rosenberg**, 2005) towards innovation performance (**Moustaghfir; Schiuma**, 2013; **Lee *et al.***, 2008). Exposure to different skills and ideas helps people develop a broader understanding beyond their primary areas of expertise, leading to better, more innovative approaches to IT challenges. For these reasons, it is believed that effective learning is a crucial indicator for improving learning exposure, specifically for those linked to the information technology firms' research and development departments.

5. Conclusion

Improving the employees' learning exposure is a better pathway for achieving greater organizational success. However, this achievement is primarily linked with so many critical factors which need to be considered by policymakers, management executives, and other officials. Considering the information technology firms, it is widely recognized that innovation is the key to success. Therefore, focusing on effective learning, problem solving, artificial intelligence learning, digital literacy, and information stewardship can generate substantial results for strategic policymaking. This research has been conducted on the key firms linked with the IT sector, and the results were generated using the most advanced technique, structural equation modeling. The results confirm that an increase in the learning exposure of the given sample from the R&D departments of the IT firms is mainly connected with information stewardship, effective learning, and artificial intelligence learning. These factors highlight the path for the several policy implications specifically for the information technology department and in general, for the other firms working in a similar domain or the industry in different regional settings.

This study recommends to focus on the relationship between artificial intelligence learning and learning exposure. For this objective, the study suggests that the key officials and managers in IT firms and their research and development departments need to create AI-driven personalized learning systems for several strategic reasons. For instance, these systems would suggest specific training for each employee based on their role and organizational responsibilities, skills, and expertise, which are linked with different innovative projects. Moreover, artificial intelligence can analyze their work data to find skill gaps and recommend courses or resources to create a synergetic effect. This way, employees and key individuals linked with the R&D departments to get the right training for their needs, saving time and making learning more effective. By using the virtual assistants and chatbots linked with the AI, the employees could also quickly access learning materials and technical help whenever they need it. AI can also help through collaboration and knowledge-sharing platforms. AI can connect employees with similar interests or skills, encouraging them to work together and share ideas. It can also help organize internal resources, like research papers or project data, making finding information relevant to ongoing work easy. This setup allows employees to learn from each other's experiences and stay updated on new developments in technology. By creating easy access to useful information and linking people with shared expertise, AI can boost the team's knowledge and help them create innovative solutions.

The study also recommends to focus on causing effective relationship for learning exposure of employees As an example, effective learning means not only gaining knowledge and information but also applying it in practical ways. LOU, on the other hand, is about the opportunities employees have to learn from various sources, some good experiences, and challenges related to different tasks. When learning is effective, it improves the value of each learning opportunity while helping the key employees linked with the IT firms and R&D departments in terms of new skills. In turn, increased LOU gives the employees of the R&D department with a wider range of experiences, which supports more effective learning. Furthermore, collective, the employees in the R&D departments can effectively capture the learning strengthens and increased exposure which can encourage the continuous growth. The study also recommends for companies to initiate key practices for effective learning. For instance, tailored training programs can be designed to ensure that employees receive learning experiences suited to their skill levels and roles, making learning both relevant and impactful. Opportunities can be created for hands-on learning, through projects or challenges that apply new skills directly to their work. Companies can also encourage mentorship programs where experienced employees share their knowledge, exposing others to real-world insights. By combining targeted training, practical experiences, and mentorship, companies can support effective learning while expanding the learning exposure for everyone as working in the R&D departments of the information technology firms.

The study connects this debate with some of the limitations faced in this study. The first limitation was that this study had completely focused on IT firms and their R&D departments while ignoring other sectors like education, manufacturing, banking, and business organizations, including retail and small units. Future studies can implement qualitative techniques or meta-analyses regarding the trends and gaps in learning exposure, information stewardship, affective learning, and learning through artificial intelligence. By addressing these limitations, future studies can expand the implications and practical suggestions related to the given topics and field of interest.

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