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Understanding Digital Library Use among STEM and Non-STEM Students: Insights from PLS-SEM MGA

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***Abstract* - Digitalization has transformed education globally, with Digital Library Remote Access (DLRA) services offering seamless access to literature and scientific resources. This study examines the factors influencing DLRA usage behavior in a prestigious Indian private higher education institution. Using a sample of 400 researchers and students, the research investigates the factors influencing DLRA adoption among STEM and Non-STEM respondents. The data were investigated employing Partial Least Squares – Structural Equation Modeling Multi-group Analysis using SmartPLS software version 3. Findings reveal notable variations in social influence, facilitating conditions, habit, and usage patterns of STEM and Non-STEM participants. The novel study contributes to library and information science literature as well as technology adoption literature by exploring the differences among the factors influencing DLRA adoption among STEM and Non-STEM researchers and students.**

***Keywords:* Digital Library, Multi-Group Analysis, STEM, Non-STEM, Usage Behavior**

I. INTRODUCTION

A technological revolution in education has been brought by the COVID-19 pandemic. This prompted the quick adoption of remote learning. Remote learning has ensured continuance of education among uncertainties (Sumithra & Sakshi, 2024; Anthony Jnr & Noel, 2021; Manca & Delfino, 2021; Oliveira et al., 2021; Ali, 2020; Dubey & Pandey, 2020). Digital library access has been central in facilitating education in the higher education context (Sumithra & Sakshi, 2024; Yu, Xu & Yu, 2022; Ćirić & Ćirić, 2021; Bhati & Kumar, 2020; Mehta & Wang, 2020). The digital library is viewed as both a source of information and an information system (Sing Yun, 2023; Radina & Balakina, 2021; Amankwah-Amoah et al., 2021). Research predicts digitalization and the adoption of digital libraries is the way to renew and sustain higher education (Kasmia & M'hamed, 2023; Bygstad et al., 2022). Institutions are assured to deploy technology to improve the educational experience (Ahmad, 2020). An open remote access research depository of e-resources is maintained by the National Digital Library of India at IIT Kharagpur to facilitate academic and research activities by students, faculty, scientists and researchers (Sumithra & Sakshi, 2024; Singh, 2022).

The objectives of Library and Information Science (LIS) research have encompassed so many theories to explain several factors affecting user behaviour in library. As we have already pointed out, LibQUAL is currently the most frequently addressed area of interest by LIS researchers which is centered on factors that influence and the users' perception of quality of library services (Clifford Ishola et al., 2023). A number of scholars Wu, Yuan and Tsai in 2020 noted that literature on the subject of LibQUAL scale is still limited but available studies indicating the application of LibQUAL scale in library context includes McCaffrey in 2013, Greenwood et al., in 2011. DigiQUAL is another frequently used and tested and validated scale in LIS research. Such studies concern the impact of digital technology in relation to library services and how that could expand its utility. Notable work done in this particular context is the work done in year 2012 by Naiich et al. and in 2014 by Jafarbegloo et al. Further, the ServQUAL model, which affects the library services, was explored in the Asogwa et al research conducted in 2014 while Cook & Thompson conducted a study in the year 2000. This popular paradigm assists libraries in gaining a better insight into how people perceive the products that they provide. Besides these, numerous other theories, related to user satisfaction have been studied within the undercurrents of LIS. These theories assist in explaining the quality of good library services and assist in identifying modifications that could be implemented so as to improve on the existing services in order to meet the needs of the patrons.

Technology integration is one of the most sensitive issues in organization because it is the product of a numerous factors. These criteria can be broadly classified into four categories: It includes the considerations on users, organization readiness, economic factors, and technology aspects (Blazic et al., 2023). Technology-related features are mostly composed of the ease of use perceived by the user and the perceived usefulness of the technology. Relevant to (Davis, 1989; Adams et al., 1992; Joo & Choi, 2015), established the fact that, if a technology was perceived to be easy to use and necessary, it would likely to be accepted. This has a bearing in meaning that for the technology to be accepted the technology must be useful and easy to use. Another factor that greatly affects the adoption of technology is the economic factors like how useful is the technology. While choosing whether to adopt a specific technology several factors can come into play due to the possible economic returns that may be experienced for example organisational cost reduction or increase in productivity as postulated by (Huijts et al., 2012). As (Lin et al., 2007) point out, another aspect is organizational readiness to make necessary changes and support people's development. This kind of response relates to the organization's willingness and preparedness to embrace as well as accommodate new technology. Factors that may affect an organisation's ability to accept new technology include: Physical acess to setup, consultancy and, training. Other important user criteria include user's perceived ability and gender attitude as far as technology is concerned. The literature review encourages the acceptance of knowing that individuals' attitudes towards technology, and self-efficacy beliefs affecting its usage have a strong connection with the adoption of technology (Kim et al., 2009; Sumithra & Sakshi, 2024; Hussein, 2017; Kulviwat et al., 2014; Yang & Yoo, 2004).

This paper adopted the Universal Theory of Acceptance and Use of Technology 2 (UTAUT2) which has become the framework adopted in current research in technology acceptance and use in diverse organisations. In the context of the UTAUT2, Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Hedonic Motivation, Price Values, as well as Habit can influence Behavioral Intention and Use Behaviour for adopting technologies while Age, Gender and Experience as the moderator variables (Ling et al., 2012). This paper is relevant to digital public services, e-procurement in the construction industry, mobile banking, and educational contexts (Dionika et al., 2020; Addy et al., 2022; Yaseen et al., 2022; Or, 2023). Subsequently, UTAUT2 has been adopted to predict acceptability of mHealth, social commerce and post-bariatric surgical therapies (Schretzmier & Hecker, 2022; Shoheib & Abu-Shanab, 2022; Thérouanne et al., 2023). The technology acceptance with consideration to the UTAUT2 model reveals global influence by Tamilmani et al. (2020) as comprising of trust, personal innovativeness, and perceived risk (Tanja & Milica, 2023). This versatility makes it safe to use at the different geographic regions and technical disciplines due to findings on blended learning, animations, and mobile technology acceptance among educator (Dakduk et al., 2018; Dajani & Hegleh, 2019; Omar et al., 2019). Mobile banking applications' adoption has been enhanced by the addition of trust factors. Therefore, the developments that occurred in UTAUT2 established a more robust framework of Technology Acceptance that is contextually usable in different domains and with different users, thus useful for both theorists and applied researchers in the field inclusive of marketing practitioners.

It is noteworthy that there are three options for undertaking research using the UTAUT2 model, however, partial studies are emphasized in the literature (Kułak et al., 2019). This study aims to profoundly investigate the part of selected UTAUT2 features, namely: influence of social, facilitating conditions, hedonism and habit in determining the usage of a technology. Building upon the work done by Sumithra & Sakshi in 2024, this study focuses on the appreciation of the STEM (Science, Technology, Engineering and Mathematics) and Non-STEM difference in the factors influencing behavioral intention to use and self-reported use of Digital Library Remote Access (DLRA) technology (Arora, 2024). In this way, the research of these variables aims to gain understanding of how specific parts contribute to DLRA technology adoption, and how these impacts within and across STEM and non-STEM groups (Veysi & Salari-Aliabadi, 2021). This may help guide the specific utilization and adoption of the technology as a whole throughout the DLRA in a manner that would possibly enhance acceptance. The current study aims to investigate the dynamics of UTAUT2 model selective factors, namely: interpersonal influence, attitude, perceived usefulness, and hedonic reasons towards the intended use and subsequent use behavior towards DLRA technology among STEM and non-STEM patronss (Sumithra & Sakshi, 2024; Pilotti et al., 2024).

A breakdown of DLRA indicates that the decisions made by the patrons regarding the technological platforms are in the context of the technological savoir faire indicated by the science and technology patrons. STEM education includes the use of technology since technology is generally utilized in teaching and mastery of STEM, which increases patrons' technical proficiency in the use of gadgets alongside making them feel comfortable utilizing gadgets (Vahidy, 2019). This skill influences the success of participating Digital Libraries that include learner-learner and learner-instructor discussion, additional resources, and timely cooperative settings. Such kind of platforms has capacity to address the various learning styles of learners and also addition of graphics helps to improve the learning and assist in engagement by (Vahidy, 2019). The technical expertise for working in the digitally driven environment particularly in coding is crucial among the STEM patrons (Vieira et al., 2023). Yet these are assumption that should be treated as hypotheses and empirically examined within research on the topic. STEM and non-STEM patrons use different resources and this may also influence their behaviour concerning the technology of DLRA. STEM patrons may have to encounter like scientific journals, technical papers, databases, technological instruments present in the article of digital library. STEM patrons require concept repetition that involves technology in which there are virtual simulations and instructional games as observed by (Vieira et al., 2023). This evidence, where STEM patrons may require more specific information most of the time and can use digital sources proficiently, demonstrates that the non-STEM patrons may require quite a different kind of resources – books, articles, multimedia, which is a rather broad category. Patrons in humanities and social sciences may require sources of information that may comprise of history and social science documents and literature compilations. They may obtain benefits and facilities through composing and communicating tools which form citation genitors, application checkers, and presentation tools (Krueger, 2017). Based on the abovementioned assumptions about the distinctions between STEM and non-STEM patrons in terms of the load/necessity for employing resources, their digital library's utilization/engagement may be critically challenged, which once again points to the need for actual research.

The very nature of learning methods used in both STEM and non-STEM education causing unequal distribution of digital library usage. STEM education may place the emphasis on problem-solving and skills acquired through practical practice, and in this sense, digital libraries reinforce the ideas making use of interactive materials and methods as well as real-time collaboration tools. Such presentation methods as diagrams and other tools enhance the comprehension of abstract concepts, and create cooperative learning environments while being perfectly in line with STEM patrons' choice (Saetang et al., 2023). The differences in the learning outcomes of patrons in STEM and non-STEM courses support this notion, as the non-STEM courses are usually broader and less detailed, thus patrons might not require the same level of exposure to the digital library (Owston et al., 2020). Based on the learning styles of non-STEM patrons in the humanities and social sciences, such patrons may rely more on reading and writing abilities, and since digital libraries can offer large compilations of textual resources, they may suit non-STEM patrons well (Saetang et al., 2023). As such, although the presence of learning style differences between STEM and non-STEM patrons has a significant influence on their use and engagement with digital libraries, there is a need to conduct research to provide evidence for these research hypotheses (Saetang et al., 2023; Owston et al., 2020).

In this research, the researcher wants to examine the variations in the BI and actual behavior of patrons from the STEM and non-STEM backgrounds when using digital library platforms as the literature emphasizes that differences have been observed consistently when STEM and non-STEM participants are involved in various activities. The research is also relevant as it also focuses on differences in technology usage amongst STEM and non-STEM library patrons in DLRA. STEM patrons are likely to use DLRA technology to access scientific journals and other resources required for their coursework (Cooper & Springer, 2019; Kim & Zhang, 2015; Zilinski et al., 2014; Mardis, 2014), while for non-STEM patrons, they are likely to use DLRA technology to obtain books, journals, and other basic references of humanities and social sciences (Xu, 2022; Barboza & Teixeira, 2020).

Therefore, there is cross-sectional variation assumed regarding DLRA technology usage by patrons belonging to various educational stream. The findings of this study augment knowledge in LIS hence the identification of the differences between STEM and non-STEM patrons in dynamics that affect behavioural intention and use behaviour this research also aids technology adoption literature in pinpointing the needs of STEM and non-STEM participants in possible assist the technology industry to broker user sensitive experience design. With these significant differences of the overall dynamics of perceived convincibility, anticipated self and peer approval, societal norms, hedonistic appeal, and habit impacting on the behavioural intention and usage of DLRA technology, the study contributes value insight in influencing numerous determinants associated with LIS and technology acceptance. Therefore, the interaction among different factors defines the distinct utilization trends of digital libraries between STEM and Non-STEM patrons. Hence, with the aim to arrive at a thorough comprehension of the factors impacting technology adoption and usage (see Figure 1), empirical research is essential for confirming and clarifying the observational differences among STEM and Non-STEM patrons. Thus, we propose:

H1: There is significant difference among STEM and Non-STEM respondents in Facilitating Conditions influencing Behavioral Intention of DLRA technology

H2: There is significant difference among STEM and Non-STEM respondents in Habit influencing Behavioral Intention of DLRA technology

H3: There is significant difference among STEM and Non-STEM respondents in Hedonistic Motivation influencing Behavioral Intention of DLRA technology

H4: There is significant difference among STEM and Non-STEM respondents in Social Influence influencing Behavioral Intention of DLRA technology

H5: There is significant difference among STEM and Non-STEM respondents in Behavioral Intention influencing Usage Behavior of DLRA technology

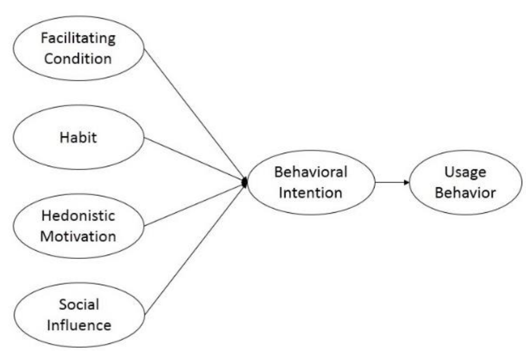

Fig. 1 Conceptual Framework

(Source: Adopted from Sumithra & Sakshi (2024))

II. METHODS

This study purports to investigate how the facilitating conditions, habit, hedonism and social influence impact the behavioral intention and actual usage behavior of both STEM and Non-STEM patrons when utilizing DLRA technology, descriptive study is deemed as the appropriate approach to fulfill the study purpose. This study borrowed survey questions from a model framed by Venkatesh et al. (2012) to measure user intention. It's important to adjust these questions to fit the specific technology being studied, like DLRA. This cross-sectional descriptive study utilizes purposive sampling, selecting 400 individuals from users of DLRA technology, comprising patrons and researchers from a private higher education institution in India. This institution is a deemed to be university, recognized as an institution of eminence, offers remote access to its digital library materials. Data were amassed using an organized questionnaire through the survey technique. Thus, collected data underwent assessment of reliability of each item and the degree to which the measurement items align with other established measures within each construct of the measurement model.

Compared to other structural equation modeling methods, partial least squares-structural equation modeling empasizes maximizing the explained inconsistency of dependent variables to optimize the forecast of contributory interactions (Ghazali et al., 2020; Hair et al., 2012). Hence, PLS-SEM was selected not only for its ability to assess multiple constructs simultaneously but also aimed at its capability to perform multi-group analysis (MGA) via the Measurement Invariance of Composite Models (MICOM) procedure (Ghazali et al., 2020). MICOM enables the evaluation of invariance in PLS-SEM. MGA allows researchers to compare identical models across distinct sets and recognize dissimilarities in mechanical paths. Moreover, the MGA examines whether predefined groups exhibit significant differences as indicated by group-specific factor approximations. The robustness of PLS-MGA results was ensured using MICOM, the permutation technique, and PLS-MGA (Ghazali et al., 2020; Basco et al., 2020; Rasoolimanesh et al., 2017). Despite deviations from normality, PLS-SEM remains robust in handling multifaceted facsimiles and non-normal data dispersals, unlike CB-SEM, which requires multivariate normality (Rigdon, 2016). SmartPLS Version 3.2.8 (Ringle et al., 2015) was engaged for data examination. Multi-Group Analysis was expended to examine the alterations between STEM and Non-STEM users of DLRA technology.

TABLE I EDUCATIONAL STREAM PROFILE OF RESPONDENTS

Demographics	**Criteria**	**No.**	**%**
Stream	STEM	212	53
	Non-STEM	188	47
TOTAL		400	100

The demographic character, which is the stream of education or research of the survey participants are exhibited in Table I, comprises of 400 respondents, of whom 53% STEM and 47% Non-STEM stream patrons and research scholars of the private higher education institution in India.

III. RESULTS AND DISCUSSIONS

The outerloadings and VIF values all met the threshold level (see Table II). With 1 item, FC2, whose VIF value, was above the threshold, 5 and 1 item, UB4, whose outerloading, was below 0.5, were excluded from the study (Hair et al., 2019) and hence the measurement tool was deemed to be fit, with multi-collinearity issue under control.

TABLE II OUTER LOADINGS AND VIF VALUES OF EACH ITEM

	BI	FC	HM	HT	SI	UB	VIF
BI1	0.946						4.745
BI2	0.797						1.637
BI3	0.921						4.184
FC1		0.904					4.803
FC2		0.923					5.134
FC3		0.893					3.109
FC4		0.834					2.331
HM1			0.909				2.633
HM2			0.906				2.981
HM3			0.869				2.027
HT1				0.809			2.376
HT2				0.809			2.269
HT3				0.841			2.056
HT4				0.893			2.547
SI1					0.923		2.803
SI2					0.819		1.783
SI3					0.874		2.203
UB1						0.931	3.237
UB2						0.945	4.323
UB3						0.881	2.903
UB4						0.495	1.294

The study results confirmed the consistency of the constructs, surpassing the threshold level. The Cronbach's alpha values exceeded the threshold (Hair et al., 2019), ensuring reliability. Similarly, the composite reliability between the study's constructs met the threshold (Hair et al., 2019). The AVE as well surpassed the threshold level (Hair et al., 2019; Bagozzi & Yi, 1988). Altogether the consistency and validity exams unequivocally indicate the cohesiveness of the items within the constructs, demonstrating reliability and convergent validity.

TABLE III MEASUREMENT MODEL

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BI	0.866	0.876	0.919	0.792
FC	0.867	0.868	0.919	0.791
HM	0.876	0.889	0.923	0.801
HT	0.862	0.884	0.905	0.704
SI	0.843	0.853	0.906	0.762
UB	0.911	0.952	0.943	0.847

TABLE IV INTER-CONSTRUCT CORRELATIONS

	BI	FC	HM	HT	SI	UB
BI	0.89					
FC	0.756	0.889				
HM	0.477	0.348	0.895			
HT	0.813	0.781	0.377	0.839		
SI	0.806	0.545	0.585	0.614	0.873	
UB	0.395	0.246	0.084	0.437	0.432	0.92

Discriminant validity is established by ensuring that the associations among variables are lesser than the square root of the AVE for each variable. Additionally, the construct's items have higher cross-loadings compared to those of supplementary constructs, satisfying the Fornell-Larcker Criterion (Fornell & Larcker, 1981). The outcomes highlighted in Table III & IV underscore that the constructs have achieved discriminant validity.

TABLE V MODEL FITNESS ESTIMATES

	R Square	R Square Adjusted
BI	0.833	0.831
UB	0.156	0.154

In Table V R squared value for behavioral intention (BI) as the dependent variable is 0.833, indicating a strong association (Hair et al., 2019). This suggests that 83.3 percent of the variance in users' behavioral intention to utilize digital library resources is collectively accounted for by social influence, facilitating conditions and habit, which echoes the literature evidence of Sumithra & Sakshi, 2024. Behavioral intention explains 15.6 percent of the change in use behavior of DLRA technology, which means that, there are other uncaptured factors that influence use behavior, other than behavioral intention (Hair et al., 2019).

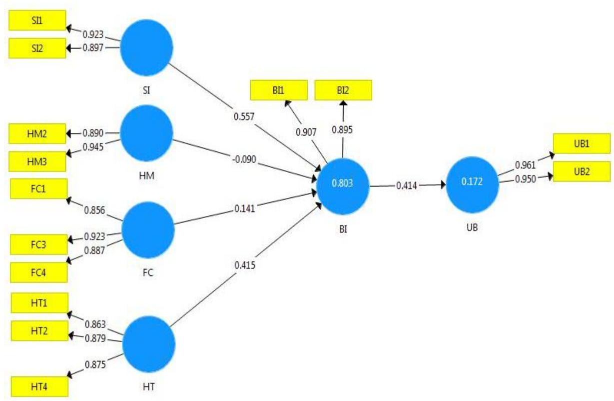

Fig. 2 STEM Path Diagram

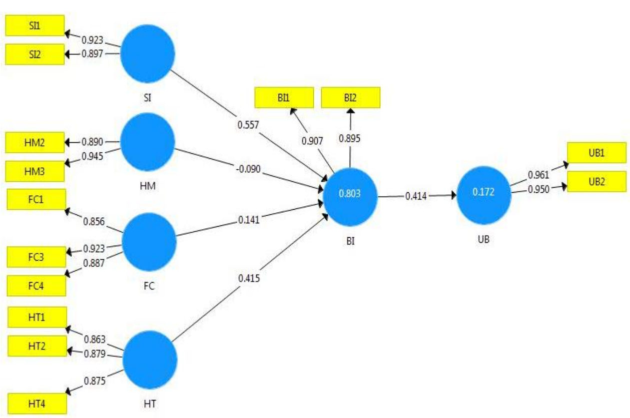

Fig. 3 Non-STEM Path Diagram

TABLE VI PATH COEFFICIENTS

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	TStatistics (|O/STDEV|)	P Values
BI ->UB	0.395	0.398	0.043	9.186	0
FC ->BI	0.232	0.234	0.032	7.216	0
FC ->UB	0.092	0.093	0.015	6.036	0
HM ->BI	-0.011	-0.011	0.035	0.323	0.747
HM ->UB	-0.004	-0.004	0.014	0.322	0.748
HT ->BI	0.344	0.341	0.035	9.823	0
HT ->UB	0.136	0.136	0.021	6.568	0
SI -> BI	0.475	0.477	0.04	11.98	0
SI ->UB	0.188	0.19	0.027	7.077	0

The findings from Table VI, Figure 2 and Figure 3 indicate a significant and positive impact of facilitating conditions ($\beta = 0.232$, $t = 7.216$), habit ($\beta = 0.344$, $t = 9.823$), and social influence ($\beta = 0.475$, $t = 11.98$) on the behavioral intention of DLRA technology users. Also, it is worth bearing in mind that the path coefficient for the hedonism construct is negative and statistically insignificant. Moreover, the effects of facilitating conditions, habit, social influence, and behavioral intention positively and significantly impact user behavior regarding digital library resources ($\beta = 0.395$, $t = 9.186$).

Measurement invariance across subgroups is a prerequisite for MGA. This ensures that any disparities in model assessment parameters between subcategories are not a result of any differences in how the groups understand the meaning of the measures used in the model (Ghazali et al., 2020). It is central to distinguish that failure to establish measurement invariance can inflate measurement error, potentially leading to bias in the results (Ghazali et al., 2020; Hair et al., 2017).

Our initial analysis indicated that some constructs lacked compositional invariance. To address this and ensure consistent measurement, we removed certain items following Hair et al. (2017) and Ghazali et al. (2020). These items (BI3, FC3, HM1, HT3, SI3, and UB3) were statistically distinct ($p \leq 0.05$). Removing these items made sure all the questions within each group contributed equally to the overall score (called construct). This helped us achieve consistency in how the scores were interpreted across different groups (Ghazali et al., 2020; Dijkstra & Henseler, 2011). Subsequently, each construct successfully passed through the initial and subsequent stages of MICOM, confirming partial invariance. Following the establishment of partial invariance, multi-group analysis was conducted to match path coefficients between STEM and non-STEM respondents in forecasting DLRA usage behavior.

TABLE VII HYPOTHESIS TESTING RESULTS

	Total Effects Original (NonSTEM)	Total Effects Original (STEM)	Total Effects Mean (NonSTEM)	Total Effects Mean (STEM)	STDEV (NonSTEM)	STDEV (STEM)	t-Value (NonSTEM)	t-Value (STEM)	p-Value (NonSTEM)	p-Value (STEM)
BI -> UB	0.376	0.443	0.376	0.441	0.066	0.049	5.679	8.993	**0**	**0**
FC -> BI	0.142	0.175	0.147	0.166	0.066	0.046	2.138	3.849	**0.033**	**0**
FC -> UB	0.053	0.078	0.055	0.072	0.027	0.02	1.991	3.89	**0.047**	**0**
HM -> BI	0.064	0.033	0.058	-0.048	0.077	0.093	0.83	0.352	**0.407**	**0.725**
HM -> UB	0.024	0.014	0.022	-0.02	0.03	0.04	0.802	0.364	**0.423**	**0.716**
HT -> BI	0.35	0.447	0.347	0.427	0.063	0.083	5.557	5.385	**0**	**0**
HT -> UB	0.132	0.198	0.131	0.189	0.036	0.047	3.69	4.248	**0**	**0**
SI -> BI	0.416	0.615	0.421	0.637	0.064	0.031	6.544	19.983	**0**	**0**
SI -> UB	0.157	0.273	0.158	0.28	0.034	0.029	4.589	9.361	**0**	**0**

Henseler's MGA technique identifies statistically different effects between groups by analyzing p-values of path coefficients. Values below 0.05 or above 0.95 suggest significant differences at the 5% confidence level (Ghazali et al., 2020). Our analysis, using extensive simulations (5,000 bootstraps and permutations), revealed such differences for Social Influence (SI), Habit (HT), and Facilitating Conditions (FC) (see Table VII). These factors had a statistically stronger positive influence on both behavioral intention and actual usage of the DLRA technology for STEM patrons and researchers compared to Non-STEM groups. Interestingly, the effect of Hedonism (HM) did not differ significantly between the groups. This suggests that for STEM individuals in this context, social pressure, ingrained habits, and access to resources play a more significant role in adopting and using DLRA technology than the enjoyment factor.

TABLE VIII PREDICTIVE POWER OF THE MODEL

Group	Items	RMSE	LM RMSE	PLS-LM RMSE	Q^2_predict
STEM	BI1	0.793	0.616	0.177	0.671
	BI2	0.649	0.558	0.091	0.621
	UB1	1.287	1.169	0.118	0.176
	UB2	1.15	1.04	0.11	0.134
NonSTEM	BI1	0.792	0.615	0.177	0.67
	BI2	0.649	0.559	0.09	0.621
	UB1	1.288	1.173	0.115	0.176
	UB2	1.152	1.044	0.108	0.134

Hair et al. (2019) explained that conventional indices are not well-suited for PLS-SEM because the typical measures of fit pertain more to the connection between prediction and hypothesis validation. These are the rationales that support the identified ideas to evaluate the model (Ghazali et al., 2020). To evaluate the model's predictability, we employed PLS-Predict that was developed by Shmueli et al. (2016, 2019). This technique uses a different data sample (which is the holdout sample) to make forecasts on certain items or structures. It is considered to show high predictive relevance when all indicators from a latent dependent construct in the PLS-SEM model have a lower RMSE than the LM value. Therefore, the total errors of most the PLS-SEM indicators need be less than that of the LM. On the other hand, low or no predictive capability was observed when most or all the PLS-SEM indicators are below the LM (Ghazali et al., 2020). as indicated by all the RMSE results presented in Table VIII, all of the model's results exceeded the LM in terms of predictive capabilities. This means that the models themselves are able to not only describe but forecast DLRA usage behavior, in both the original dataset and new circumstances.

Based on the study's findings, the dynamics of Facilitating Conditions, Habit, Social Influence on Behavioral Intention, and Behavioral Intention on Usage Behavior of DLRA technology differ between STEM and non-STEM participants. It was challenging to find literature supporting the observed variations in how variables affect DLRA technology adoption among STEM and non-STEM respondents due to the unique structure of the study.

First, we the study reinforces that STEM and non-STEM participants exhibit different behaviors and abilities (Bautista et al., 2021). With regard to technology usage, social influence and behavioral intention are crucial factors in technology acceptance models (Venkatesh et al., 2008). These factors can have different impacts on how people actually use technology. Applying these concepts to the use of DLRA technology, it's possible that STEM and non-STEM respondents are affected differently by social influence and facilitating conditions. The impact of social influence on technology use varies from person to person. For example, a study on system usage in Thailand found that social influence greatly influenced people's intention to use MOOCs (Chaveesuk et al., 2022). This implies that the connection between social influence and technology use can be nuanced and multifaceted. When it comes to using Digital Library Remote Access technology, it's possible that STEM and non-STEM respondents will be influenced differently by social influence.

Habits have different effects on how the participants use DLRA technology. A recent study by Lu et al. (2023) found that patrons have less effective study habits and their approach to studying varies depending on the situation. This suggests that the relationship between habits and technology use can be complex and diverse. When it comes to using DLRA technology, it's possible that habits affect STEM and non-STEM respondents differently, based on the findings of this study. Factors like their academic background, perception of the technology, and the availability of support for adopting the technology can all impact their intention to use it and how they actually use it. While there is evidence to suggest that STEM and non-STEM respondents may have different behaviors when it comes to technology use, it's important to further investigate the specific nature of these differences, especially in the context of DLRA technology (Venkatesh et al., 2008; Bautista et al., 2021).

These findings draw insights for educational institutions and society as a whole. For educational institutions, the findings can greatly impact digital curriculum development to meet the specific needs of both STEM and non-STEM patrons. For example, since STEM patrons are more influenced by social factors, incorporating more group work and shared projects into the curriculum can be advantageous. Identifying these disparities helps in allocating resources more efficiently. If the availability of certain facilities significantly affects STEM patrons' use of digital library resources, institutions can prioritize investments in those areas for STEM programs. When non-STEM patrons are less familiar with accessing digital resources, targeted interventions can be designed to encourage frequent usage which improves their learning outcomes and their perseverance in their studies. These insight helps make learning better for all by making sure both STEM and non-STEM get what they need.

IV. CONCLUSIONS

The study looked into what makes STEM and non-STEM patrons and researchers use digital library, finding many purposeful insights. First, a solid tool was made and checked to make sure it works well and is right, by taking out bits that didn't fit well or were too alike. Next, the study checked how well UTAUT2 parts (facilitating conditions, social influence, hedonism, and habit) affect both wanting to use DLRA and actually using it. Here, social influence stood out as the biggest push, having a good effect on behavioral intention for both STEM and non-STEM groups, backing up what other studies found. There were variations found in how UTAUT2 factors influenced STEM and non-STEM users. In particular Social Influence, Habit and Facilitating Conditions had positive impacts, on Behavioral Intention and Use Behavior among STEM individuals compared to non-STEM individuals underscoring the heightened significance of these aspects in influencing digital library usage within the STEM community. Conversely there was no difference observed in the influence of Hedonism, between the two groups. Moreover, the predictive efficacy of the developed models was substantiated through robust performance in both in-sample and out-of-sample scenarios, signifying their aptitude in elucidating and prognosticating user interactions within the digital library realm. Ultimately, the study underscores the imperative of tailoring strategies to promote digital library engagement by considering user backgrounds, particularly the distinctions between STEM and non-STEM cohorts, with Social Influence, facilitating conditions, and habit emerging as pivotal factors warranting focused attention within the STEM demographic.

V. LIMITATIONS

While understanding the results of this study, it is imperative to envisage numerous limitations. First, the study depends on data gathered at a particular instant in time. Given the dynamic nature of digital library remote access (DLRA) adoption, with platforms like https://infilibnet.ac.in gaining significant traction, the study's cross-sectional design presents a potential constraint. A longitudinal approach targeting diverse population segments, tracking the trajectory of technology adoption, and focusing on behavioral intention and usage behavior over time could enhance the explanatory power of various adoption factors. Additionally, survey research inherently entails the possibility of other unexplored factors influencing technology adoption behavior. Moreover, it's worth noting that DLRA technology is continually evolving, particularly in developing nations, where enhancing technology adoption behavior is crucial for sustained digital library usage. Lastly, qualitative investigations into the inspirations driving behavioral intention and usage behavior in DLRA technology adoption might provide broad insights into digital library processes and technology utilization.

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