University Students’ Perspective on ChatGPT and Technology Literacies

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Abstract

In recent years, technologies utilising artificial intelligence have gained popularity. It is common for college students to use ChatGPT when writing academic assignments. Considering the importance of technology literacy in adopting ChatGPT in academic writing, this study explored how Chatbot was used by college students in Bhutan in relation to Privacy literacy, Data literacy, Information literacy, and Technology adoption (Chatbot). Using a cross-sectional survey, the data for this study was collected using an online survey and 290 students responded. Analyses were mainly quantitative. Both descriptive and inferential statistics were reported. The findings of Mann-Whitney U test suggests that male students used more technology compared to their female counterparts and statistically significant differences were found on technological adoption between the genders. However, the results of Kruskal-Wallis H test revealed that there was no statistically significant difference across four age levels. Furthermore, results of path analyses showed significant direct relationship from Data literacy to Technology adoption (Chatbot). However, no empirical support was found for Information literacy and Privacy literacy. Taken together, the findings of this study have significance to the students, lecturers, and policy planners of the Royal University of Bhutan.

Keywords: Information literacy, data literacy, privacy literacy, chatGPT, academic writing

Introduction

The application of Artificial Intelligence (AI) in academia is a contested issue. Some consider it a digital transformation (García-Peñalvo, 2021), while others call it a digital disruption (Area & Adell, 2021; Cotton, 2023). Similarly, the use of Open AI generated chatbot ChatGPT (Generative Pre-trained Transformer) in higher education has the potential to offer a range of benefits especially in academic writing tasks. However, the use of chatbot, is seen as posing challenges in learning academic skills (Cotton, 2023). The use of ChatGPT, according to some studies, is widely common in education and has attracted significant attention and controversy. It ranges from considering it the best AI chatbot ever released to the general public (Roose, 2022) to the most catastrophic ones that predict adverse effects in the knowledge sector (Krugman, 2022). On one hand, it is reported to have educational advantages (Taecharungroj, 2023; Zhai, 2022), and has provided instructions for its use in classrooms (Lieberman, 2023). On the other hand, the use of ChatGPT in educational institutions is questioned (Herman, 2022; Marche, 2022; Stokel-Walker, 2022), and it has been banned (Ropek, 2023) due to concerns that students will automatically use it to generate essays or classwork. However, before addressing the validity of the criticisms aimed at ChatGPT, it is important to have a better understanding of the design and its relationship to the technology literacies. The newness and novelty of this technology makes it a prime example for understanding the technology adoption intention and interest among college students. Hence, the focus is on a singular emerging technology, ChatGPT.

To this end, it remains crucial to understand the beliefs about adoption of emerging technology in academic writing (Noever & Ciolino, 2022). Individual's information, data, and privacy to create a communal information institution that supports the growth and development of these literacy skills. Though there is a significant amount of research on Information literacy (IL), Data literacy (DL), and Privacy literacy (PL) as separate constructs, use of literacies in higher education institutions (HEIs) is not well understood in a developing country context such as Bhutan. Therefore, a need is felt to explore, if DL, IL, PL sufficiently measure technological adoption. Also, the use of ChatGPT has not been extensively discussed in literature, thus this topic of inquiry is largely underexplored globally. The findings of this study are expected to contribute to the growing body of research and in understanding the use of AI which is an emerging field of interest for many researchers. Most importantly, within the context of a developing nation, this study fills in the literature as well as methodological gap and is the first ever research carried out in Bhutan. Hence, the primary objective of this study was to investigate whether there were differences in Technological adoption (ChatGPT) based on gender, age, and predictability of DL, PL, IL. Other aims of this study were to understand the effects of various literacy skills on academic writing using emerging technology. This exploration aims to identify and intervene in deficient literacy skills within the colleges of Bhutan. The following research questions were examined:

1. Are there differences in male and female college students' levels of technological adoption?
2. Is there significant difference in Technological adoption, Information literacy, Data literacy, and Privacy literacy based on respondent age?
3. Can technological adoption be predicted by related factors such PL, DL, and IL.

H1. PL has positive and significant effect on TA
H2. DL has positive and significant effect on TA
H3. IL has positive and significant effect on TA.

Artificial Intelligence and ChatGPT

The discussions on AI dates back to 1950: "Are machines capable of thinking?" (Turing, 1951). Since then, many technologies have been developed that attempt to pass the Turing Test, such as ELIZA in 1966, ALICE in 1995, and Apple Siri, Amazon Alexa, and Microsoft Cortana in 2021 (Xu et al., 2021). The recent development of the AI chatbot Chat Generative Pre-trained Transformer (ChatGPT) by OpenAI, utilising GPT language model technology, enables interaction with users, producing written texts according to given instructions, articulating answers to queries, addressing follow-up questions, admitting mistakes, challenging false premises, and rejecting inappropriate requests (ChatGPT & Perlman, 2022; Kirmani, 2022; Kumar, 2023). This advancement has generated significant excitement and hysteria, as highlighted by Taecharungroj (2023). The platform reached one million users in its first week alone (Hu, 2023; Mollman, 2022; Vallance, 2022) and has gained attention across different fields, including academia, economics, social sciences, engineering, and computer science (ChatGPT & Perlman, 2022; Gao et al., 2022).

Technology Adoption

Technology Adoption (TA) research is a field that studies how and why individuals, groups, and organisations adopt and use new technologies (Venkatesh et al., 2007). Similar to the study conducted by Lund and Agbaji (2023) on technology adoption for community development, this research also helps to understand factors that influence the adoption and diffusion of new technologies and how they can be more effectively promoted in academic writing. Factors that influence technology adoption include the perceived benefits of the technology, the perceived costs of adoption, the compatibility of the technology with existing systems and practices, and the availability of social and technical support. Moreover, the level of innovation and risk associated with the technology, the level of complexity and ease of use, the level of compatibility with existing systems and practices, and the level of social influence and peer pressure also have impacts in technology adoption (Hansen et al., 2018).

Information Literacy

The Association for College and Research Libraries (ACRL, 2000) defines information literacy as the intellectual framework for understanding, finding, evaluating, and using information. Meanwhile, Livingstone et al. (2008) distinguish media literacy from information literacy as “Media literacy sees media as a lens or window through which to view the world and express oneself while information literacy sees information as a tool with which to act upon the world” (p. 106).

Numerous studies have shown the positive impact of information literacy in various areas: the interest in using ChatGPT to improve one's community is positively related to information literacy and privacy literacy skills (Lund & Agbaji, 2023); information literacy increases the likelihood of recognising fake news stories (Jones-Jang et al., 2019); and information literacy helps identify misinformation and increases the identification of accurate information, leading to a significant reduction in the sharing of misinformation (Pennycook et al., 2021). Afassinou (2014) used the SIR (susceptible, infected, and recovered) rumour spreading model and found that more educated individuals in a population have smaller final rumour sizes, while other studies found that students' information literacy levels increase as their education level progress (Bartol et al., 2018; Dolničar et al., 2020).

Data Literacy

Ridsdale et al. (2015, p.11) defines data literacy as “the ability to collect, manage, evaluate, and apply data in a critical manner.” While Bhargava et al. (2016, p198) define data literacy as “the ability to read, work with, analyse and argue with data”, Gray et al. (2018) refer to the overlap with statistical literacy. This overlap involves actively using a set of skills to understand statistical information and includes the ability to use data critically, make ethical data decisions, and address trust in data sources. Koltay (2017) examines data literacy from the perspective of researchers and data librarians and defines it as a specific skill set and knowledge base, which empowers individuals to transform data into information and into actionable knowledge by enabling them to access, interpret, critically assess, manage, and ethically use data. Data literacy is also proposed as the ability to ask and answer real-world questions from large and small datasets through an inquiry process, with consideration of ethical use of data. It is based on core practical and creative skills, with the ability to extend knowledge of specialist data handling skills according to goals. These include the abilities to select, clean, analyse, visualise, critique and interpret data, as well as to communicate stories from data and to use data as part of a design process (Wolff et al., 2016). With exponential increase in the volume of data available in the 21st century, data literacy skills have become vital in workplaces and everyday life (Cui et al., 2023), but few people possess the proper skills to handle it (Haendel et al., 2012).

Privacy Literacy

It is difficult to define the concept of privacy and determine its boundaries as concerns about privacy change according to person, time, and culture (Kaya & Yaman, 2022). Privacy literacy is defined as the ability of a person or a group of people to seclude themselves from public scrutiny or selectively protect information about (Fayad & Halim, 2023). It is increasingly acknowledged as a multidimensional and expansive phenomenon (Epstein & Quinn, 2021). It aims to empower technology users (Hagendorff, 2020) and involves selective control over the sharing of information (Trepte, 2020). Debatin (2011, p. 51) stated "privacy literacy encompasses an informed concern for privacy and effective strategies to protect it."

The study conducted by Prince et al. (2022) observed that internet users with higher privacy literacy reported increased concerns about their privacy. Many studies revealed that privacy literacy has a positive impact on diverse areas: feeling more secure on Facebook and implementing social privacy settings (Bartsch & Dienlin, 2016); achieving a limited form of negative privacy, facilitating a privacy deliberation process, and aiding in determining necessary information (Masur, 2020); being less likely to fall victim to cybercrime (Saridakis et al., 2016); and expressing increased concerns about privacy among internet users with enhanced privacy literacy. Dienlin and Trepte (2015) examined privacy types within the framework of the Facebook sample, and the results revealed that individuals' online privacy concerns, attitudes, and intentions are indirect indicators of privacy behaviour.

In contrast, Rainie and Madden's study (2015) on users' attitudes towards online privacy and anonymity noted that most users do not consider or are unaware of the available tools that can improve their online privacy. A survey of high school and college students who are members of Facebook showed that an individual's privacy concerns are only a weak predictor of their membership on social media (Acquisiti & Gross, 2005). Most users tend not to read privacy policies and the processing of personal data because they are long and cumbersome (Custers et al., 2014; Jones & Soltren, 2005; Meieret al., 2020); nearly half of the university students in the study group did not refer to the concept of privacy when using social networks (Yıldız & Kruegel 2012), social network users, although aware of all privacy violations, exhibit a low tendency to abandon internet use (Aslanyürek, 2016).

Methodology

The research employed an online cross-sectional survey design and the samples used in the studies were from the colleges of the Royal University of Bhutan and its affiliates. These colleges were chosen as the study demanded mandatory samples in higher education, however not all the colleges responded to the survey. This sample was prepared for exploratory factor analysis. It consisted of 290 students (136 male, 149 female) with ages above 18. The sample covered students with different courses and years who randomly volunteered for the survey. Details of the participant are presented in Table 1.

Table 1
Demographic Details

	N	Freq	Percent
Gender	Male	136	47
	Female	151	52
	Others	3	1
	Total	290	100
College	College of Language and Culture Studies	10	3
	College of Natural Resources	6	2
	Gedu College of Business Studies	67	23
	Gyelposhing College of Information and Technology	20	7
	Jigme Namgyel Engineering	11	4
	Norbu Rigter College	22	7
	Paro College of Education	23	8
	Royal Thimphu College	86	30
	Samtse College of Education	17	6
	Sherubtse College	28	10
	Total	290	100
Age	18-27	266	91
	28-37	19	6
	38-47	5	2
	48 and above	1	1
	Total	290	100

Data Collection and Procedures

Using a cross-sectional survey and convenience sampling technique, the data for this study was collected using an online survey and 290 students from 10 colleges responded to it. Prior to data collection, a letter of consent was first obtained from the Dean of Research and Industrial Linkages of respective colleges. The electronic survey questionnaire was administered to students only in those colleges that granted permission to distribute the survey questionnaire. When the survey was distributed, participants were informed not to respond if they did not feel comfortable. For this reason, although the survey was administered to all students, only 290 responded. The researchers ceased collecting data after the required sample size of more than 200 was met to perform the multivariate path analysis (Boomsma, 1987).

Measures

An adapted 5-point Likert scale survey questionnaire, ranging from strongly disagree (1) to strongly agree (5) was used in the study. The survey had 44 items adapted from Lund and Agbaji (2023). The first section of the survey asked for participants' demographic information (e.g., gender, college name, and age). The second section of the survey had four themes with 10 items each on technology adoption, information literacy, data literacy, and privacy literacy.

Data Analysis

For data analysis, several statistical tests were used, including SPSS version 23 and Amos version 26. First, to understand data, descriptive statistics such as mean, median, and standard deviation were examined. Then, an exploratory factor analysis (EFA) was conducted as the survey instruments were adapted, and not previously validated. Additionally, a Mann-Whitney U test was run to determine if there were differences in the dependent variable. Further, a non-parametric equivalent of one-way ANOVA, a Kruskal-Wallis H test was carried out to determine college students' engagement in technological adoption, information literacy, data literacy, and privacy literacy for four different age groups. Lastly, path analysis was also used to examine three proposed constructs for direct relationships and significance.

Results

In the following sections, the results obtained are discussed. It begins with Descriptive Analyses and Exploratory Factor Analysis. It is followed by the hypotheses testing through the Mann-Whitney U test and A Kruskal-Wallis H test. Finally, the relationships and significance of the three proposed constructs are represented through path analysis which was re-examined by Gretl programme, the regression analysis.

Descriptive Analyses

Descriptive statistics such as mean, median, and standard deviation were calculated to determine the univariate normality of the data. While there were no variables with 5% or more missing values, some outliers were detected and were imputed. The mean values ranged from 2.63 to 4.10 for 23 factored items. Standard deviation values ranged from .033 to 1.20. The values of skewness ranged from -.074 to -.977, while the values of kurtosis ranged from .009 to 1.169. Further based on the assessment of Kolmogorov-Smirnov normality test, the significance value for all four factors was < .05. The dataset for this study was assumed to be not normal and not suitable for parametric and multivariate analysis, as recommended by Kline (2016). To evaluate internal consistency reliability, Cronbach's alpha (α) was employed, with cut off values of 0.81 for PL, 0.71 for IL, 0.74 for DL, and 0.88 for TA. All computed alpha values exceeded the acceptable threshold of 0.70, as suggested by Collier (2020) and Kline (2016), indicating high reliability in the measurements.

Exploratory Factor Analysis

Since the questionnaire was adapted to suit the context of this study, an exploratory factor analysis (EFA) using a principal component analysis with varimax rotation was performed. The minimum factor loading criteria was set to 0.50. The communality of the scale, which indicated the amount of variance in each dimension, was also assessed to ensure acceptable levels of explanation. The results showed that all communalities were over 0.50.

An important step involved weighing the overall significance of the correlation matrix through Bartlett's test of Sphericity, which provides a measure of the statistical probability that the correlation matrix has significant correlation among some of its components. The results were significant, x^2 (n=290) = 3856.29 [p < 0.001] indicating the suitability for factor analysis. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA), which indicates the appropriateness of the data for factor analysis, was 0.820. In this regard, data with MSA values above 0.800 were considered appropriate. Finally, the factor solution derived from this analysis yielded four factors for the scale, which accounted for 40.087 variation in the data.

Nonetheless, in this initial EFA, from Factor One, privacy literacy, three items (i.e., PL2-*I am not sure whether the various Security Agency can track the information I am accessing on my computer*; PL4-*I believe that I can request a record of all the personal data that websites have collected about me*; PL10-*I regularly review and update my privacy settings on social media platforms*) failed to load on any factors significantly. Similarly, from Factor Two, items TA4, TA5, TA7 were removed. Likewise, from Factor Three, six items (IL1, IL2, IL7, IL8, IL9, & IL10) had to be removed due to cross-loading. And lastly, from Factor Four, again five items (DL1, DL2, DL5, DL8, & DL9) had to be discarded (see Table 2).

As required, the EFA was repeated after deleting the items indicated within the four factors above. The results of this new analysis confirmed four factors. The Kaiser-Meyer-Olkin measure of sampling adequacy (MSA), which indicated the appropriateness of the data for factor analysis, was 0.852. The factor solution derived from this analysis yielded four factors for the scale, which accounted for 53.072 variation in the data. Bartlett's test of Sphericity results showed, x^2 (n=290) = 2572.189 [p < 0.001].

Table 2

EFA Results

Items	1	2	3	4
Privacy_Literacy				
PL1	.556			
PL3	.570			
PL5	.781			
PL6	.561			
PL7	.792			
PL8	.789			
PL9	.548			
Technology_Adoption				
TA1		.803		
TA2		.565		
TA3		.835		
TA6		.800		
TA8		.844		
TA9		.660		
TA10		.884		
Information_Literacy				
IL3			.609	
IL4			.728	
IL5			.785	
IL6			.642	
Data_Literacy				
DL3				.676
DL4				.607
DL6				.644
DL7				.536
DL10				.539

Research Question 1

The Mann-Whitney U test was carried out to determine significant differences in the levels of technological adoption (TA) between males and females. Upon visual inspection, the technological adoption (TA) scores varied significantly between males and females. When compared to females, males' TA scores (mean rank = 154.87, median = 3.60) showed statistically significant differences (U = 8790, z = -2.108, p =.035, using an exact sampling distribution for U).

Research Question 2

A Kruskal-Wallis H test, which is the non-parametric equivalent of a one-way analysis of variance, was carried out to determine if the level of engagement shown by college students in technological adoption, information literacy, data literacy, and privacy literacy varied depending on their age. With a mean rank score of 173.16 for 18-27, which is the highest in this dimension, a Kruskal-Wallis H test revealed that there was no statistically significant difference in technological adoption [2(3) =.290, p =.962]. This finding was supported by the absence of a statistically significant difference in the rate of technological adoption. The table (Table 3) presents the remaining statistics for the age groups spanning from 28 to 37, 38 to 47, and 48 and older respectively.

Similarly, no differences that could be considered statistically significant were found in terms of information literacy [2(3) = 1.42, p =.70], data literacy [2(3) = 3.13, p =.37], and privacy literacy [2(3) = 5.83, p =.12] (Table 4).

Table 3

Kruskal-Wallis Ranks Test

	Age	N	Mean Rank
Technological Adoption	18-27	264	173.16
	28-37	19	150.53
	38-47	5	138.50
	48 and above	2	146.00
Information Literacy	18-27	264	145.72
	28-37	19	159.19
	38-47	5	109.60
	48 and above	2	156.00
Data Literacy	18-27	264	144.29
	28-37	19	155.19
	38-47	5	111.90
	48 and above	2	229.50
Privacy Literacy	18-27	264	148.47
	28-37	19	129.92
	38-47	5	73.80
	48 and above	2	81.25
	Total	290	

Table 4
Kruskal-Wallis Test Statistics[a,b]

	Technological Adoption	Information Literacy	Data Literacy	Privacy Literacy
Chi-Square	.29	1.42	3.13	5.83
Df	3	3	3	3
Asymp. Sig.	.96	.70	.37	.12

a. Kruskal Wallis Test
b. Grouping Variable: Age

Research Question 3

H1. PL has positive and significant effect on TA
H2. DL has positive and significant effect on TA
H3. IL has positive and significant effect on TA

Path Analysis

A path analysis was used to examine three proposed constructs for direct relationships and significance (see Figure 1). Before estimating the model's path, the multicollinearity assumptions, a Kock (2015), variance inflation factor (VIF) and tolerance were calculated using the Gretl software package to assess for PL, IL, DL, and TA. A VIF and tolerance are both measures of checking multicollinearity (Hair et al., 2019). Following the recommendation by Hair et al. (2019), VIF values accepted threshold is < 5. The collinearity statistics of where TA was taken as the dependent variable (see Table 5 for details). Further, a composite score for each item within the construct was also computed to generate VIF. The VIF and tolerance values are presented in Table 5 as well. Therefore, the generated VIF and tolerance values confirm that this study had no multicollinearity issues.

Table 5
Collinearity Statistics

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	PL	.87	1.14
	IL	.94	1.06
	DL	.83	1.20

Dependent Variable: Technological adoption

Hypothesis Testing

We examined three direct relationships, and the results of hypothesis testing are presented in Table 6. Out of three proposed hypotheses, H2 received empirical support, while H1 and H3 did not, leading to their rejection. The detailed estimates (β), critical ratios, and *p*-value are presented in Table 6). Alternatively, using the Gretl programme, the regression analysis was re-estimated, which resulted in the same *r*- square value of 11.4 % variance in the technological adoption by the college students of RUB and its affiliates, for details see Figure 1.

Figure 1
Path Analysis

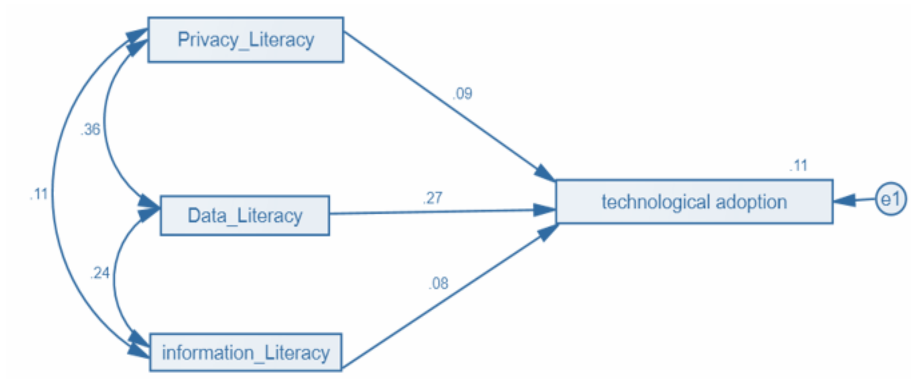

Table 6
Direct effects with a 95% Confidence Interval

Relationships	B	t-values	p-value	Decision
1 PL>TA	.09	1.52	.13	Not Supported
2 DL> TA	.27	4.36	.001**	Supported
3 IL> TA	.08	1.42	.16	Not Supported
R^2			.117	

*Note. Critical ratios are significant at [*p<.05; **p<.001; p < 0.001]; CR (t- values) exceeding 1.96 PL=Privacy literacy, DL=Data Literacy, IL= Information literacy, TA=Technology Adoption (Chatbot)*

Discussion and Conclusion

The objective of the study is manifold. First, the study was conducted to determine college students' technology adoption in academic writing and technology literacy (information literacy, data literacy, and privacy literacy) with respect to age and gender. However, the results of exploratory factor analysis (EFA) could not support the 44 items proposed by Lund and Agbaji (2023), despite modifications to align with the Bhutanese HEI's context. The study validated support for only 23 items, prompting concerns about the reliability of the items, resulting in the deletion of over 50% of the initially proposed items. We posit that the shortened version of our instruments could prove valuable for subsequent studies in a similar field, as four extracted factors for the scale accounted for 53.072 variation in the data.

The results of Mann-Whitney U revealed statistically significant differences between male and female in the study. Findings of extant literature showed that the gender differences in engaging in Information Communication Technologies are pervasive (Acilar & Sæbø, 2023). Similarly, gender gaps were also reported by Chen et al. (2023) study, and difference in the use of technology was also noted in the context of Malaysian secondary students, where males were found to be more interested in technology use, such as social networking sites (Ng et al., 2022). With respect to the findings of the study, it is anticipated that men, in the context of HEI, are more likely to explore their interest in gaming and computer related tasks. While this assertion may not be conclusively proven, we believe that males pay a lot of attention and sustained engagements in using computer devices. However, these stereotypical beliefs may soon diminish (Morris et al., 2005). For instance, the scores for technological adoption for males (median= 3.60) were statistically significantly higher than for females (median=3.40). In this case, the result mirrors the findings of Lund and Agbaji (2023), where gender was one factor that influenced the relationship between technology literacy and technology adoption. According to Okuda (2020), technology use in Bhutan is still at an infancy stage, and this may have bearing on the technology use. However, within the samples of the study, it was observed that more males engage in and adopt technology. Likewise, irrespective of gender, respondents in the study showed that more than 59 percent indicated the use of ChatGPT in the process of generating assignments for grading. Further, close to 80.5% of respondents expressed their intention to use technology in their academic pursuit and life-long learning.

The results also suggest that age did not have a difference in technological adoption, privacy literacy, data literacy, and information literacy. Therefore, age is not a concern in determining college students' engagement in technological adoption, information literacy, data literacy, and privacy literacy for four different age groups; unlike in studies that reported statistical significance in the use of technology by age (Smith et al., 2003) with a mean rank score of 173.16 for 18-27, which is the highest in this dimension. It could be that for a developing country such as Bhutan, age may not be a decisive factor in technology adoption. However, younger generations (age 18-27), who are exposed to technology, may in the times to come, increasingly adopt or engage in technology. Also, it is noticeable that those in the young age groups seemed to be concerned about privacy, compared to all age groups while using technology. However, students ranging in age from 48 and above had highest data literacy compared to others.

In contrast to the study by Lund and Agbaji (2023), where the use of ChatGPT to improve community development, was positively related to IL and PL, but not significantly related to DL; the path analysis results of this study revealed that DL had significant relationship in adopting Chat GPT in academic writing, with no positive relation to PL and IL. In this instance, the findings differ from those of Lund and Agbaji. As a result, out of three proposed hypotheses, H2 received empirical support, while H1 and H3 were rejected. Therefore, Koltay's (2011) assumption of data literacy and privacy literacy as more of "technology-based" was not supported. Consequently, it makes sense to conclude that students with higher data literacy could have more reluctance to adopt technology.

Implications of the Study

This current study has implications for faculty members working in higher education institutions in Bhutan and other countries with cultural contexts similar to Bhutan's. According to the findings of the research, more than 59 percent of respondents indicated that they make use of ChatGPT to generate assignments for grading. Similarly, 80.5% of respondents reported that they would be extremely interested in using ChatGPT in their academic writing. This suggests that students at the college level are turning in assignments generated by AI, which is a form of academic dishonesty, similar to contract cheating, pervasively practiced all over the world. As a result, faculty members are cautioned to be careful of such unethical practices and to equip themselves with sophisticated plagiarism detecting tools. Additionally, the prerequisite for faculty members to raise awareness may be an important precursor. This study has implications not only for funding agencies but also for the presidents of colleges in Bhutan, highlighting the necessity of providing professional development programmes to the country's faculty members. Lecturers' understanding of *GPTZero AI- Generated-Content Check* introduced in January 2023; *PlagScan*, and other established plagiarism checks tools may be worth exploring. Students could also participate in awareness programmes such as these in order to raise their sensitivity about the need for cautious use of textual content generated by AI and the potential consequences of doing so.

Limitations and Future Research Directions

Despite the fact that the instruments that were utilised in this research were modified, the final 23 items may still be applicable to studies conducted in countries and settings that are comparable to Bhutan. There is potential in continuing to expand the use of these items considering they have been deemed to have acceptable fit and reliability (See Appendix 1). However the method of data collection was cross-sectional, and the responses were self-reported; consequently, extreme caution is required when interpreting the results of the study. Furthermore, the study relied solely on quantitative methods for data collection and analysis purposes; future research could make use of mixed method study designs, particularly for the purpose of data triangulation and deeper understanding. Most importantly, it is recommended that both researchers and practitioners evaluate and validate the current instrument through the use of reliable multivariate testing. In addition, conducting a comparative study between college students who are users and non-users of ChatGPT is suggested. Additionally, exploring perspectives on the use of ChatGPT between lecturers and students presents potential research areas for the future.

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APPENDIX 1

Items	1	2	3	4
Privacy_Literacy				
PL1: I know how to access the browsing history on my favourite web browser.	.556			
PL3: I am not sure whether the various Security Agency can track the information I am accessing on my computer.	.570			
PL5: I know which web browsers are more secure than others.	.781			
PL6: I always read the privacy policy or statement for the websites that I use.	.561			
PL7: I feel confident that I know how to protect my personal information when using the internet.	.792			
PL8: I am familiar with the privacy settings on the websites and apps that I use.	.789			
PL9: I am aware of the potential risks of sharing personal information online (e.g., identity theft).	.548			
Technology_Adoption				
TA1: I am very interested in using ChatGPT in my academic writing.		.803		
TA2: I have used ChatGPT before.		.565		
TA3: I think ChatGPT would be a useful resource for my Academic Writing		.835		
TA6: I am comfortable with using Chatbot technology in general.		.800		
TA8: I would be willing to help promote ChatGPT in the college.		.844		
TA9: I have suggestions for how ChatGPT could be used in academic writing.		.660		
TA10: I am likely to recommend ChatGPT to be used in academic writing		.884		
Information_Literacy				
IL3: I find it challenging to decide what keywords to use for online searches.			.609	
IL4: I am not sure whether the information I find online is reliable or not.			.728	
IL5: I am always skeptical of the information I encounter.			.785	
IL6: I look for answers to questions across multiple sources before forming an opinion.			.642	
Data_Literacy				
DL3: 25. I know how to use Microsoft Excel to add, subtract, multiply, and divide a set of numbers.				.676
DL4: I would prefer to read a summary of findings from a survey and never look at the details myself				.607
DL6: I feel confident in my ability to analyze and interpret data.				.644
DL7: I often have difficulty understanding data visualizations.				.536
DL10: I am familiar with different sampling methods (e.g., convenience, random, stratified).				.539