International Journal of Multidisciplinary Research and Publications
ISSN (Online): 2581-6187

Examining Students' Awareness and Utilization of Optical Character Recognition Tools

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Abstract**—***This study explores students' awareness and utilization of Optical Character Recognition (OCR) tools through the lens of the Technology Acceptance Model (TAM), a well-established framework that elucidates technology adoption behaviors. OCR technology has become essential, enhancing accessibility in academic settings. The descriptive statistics and structural equation modeling give bits of knowledge into levels of awareness and utilization. Results show that all the variables measured demonstrated very high levels of perceived characteristics. The Perceived Usefulness has a median of 4.58 with a standard deviation of 0.5, Perceived Ease of Use has 4.22 with a standard deviation of 0.69, Behavioral Intention of Use has 4.39 with a standard deviation of 0.57, while External Variables have a mean of 3.65 with a standard deviation of 0.72. The total mean of 4.21 and a standard deviation of 0.62 demonstrate a reliably positive and exceptional recognition of all factors. Additionally, the accuracy rate of the OCR tool was achieved over 90% in multiple cases; six (6) tests recorded accuracy rates below 50% and nine (9) tests were 100% in handwritten tests, highlighting the struggles in processing poor or irregular handwriting, including cursive styles, overlapping characters, or noisy backgrounds. These discoveries emphasize the need to focus on preparing and bolstering to improve students' competency and confidence in utilizing OCR tools. The study underscores the potential of OCR to support inclusive and efficient learning environments to improve training, integration, and policy support to foster greater student engagement with OCR technology.*

Keywords— *Optical Character Recognition (OCR); Student Awareness; Technology Acceptance Model (TAM); OCR Utilization.*

I. Introduction

The application of OCR technology within educational contexts accelerates the digitization of textbooks, research papers, and handwritten notes, enabling easier distribution and improved student interaction with educational content (Gowrishankar, 2023). It supports processes like automated grading, knowledge extraction, and content analysis, which collectively enhance academic efficiency and reduce administrative burdens on educators (Zulhijar et. al., 2025). Additionally, OCR's capability to convert physical educational resources into editable and searchable digital data is fundamental to advancing e-learning, hybrid learning environments, and innovative educational communication tools (Semenist & Makhachashvili, 2021; Kaliyeva et.al., 2023). This function not only promotes accessibility for varying learners but also improves document handling and enhances research processes. As educational institutions increasingly integrate digital resources, understanding the factors influencing students' acceptance and use of OCR tools becomes essential (Amanda Levay, 2025). One theoretical framework that has been widely employed to explore technology adoption in educational contexts is the Technology Acceptance Model (TAM). Initially proposed by Davis in 1989, TAM explains users' acceptance of technology through perceived usefulness and perceived ease of use, which subsequently shape attitudes and intentions towards technology use (Hubona & Whisenand, 1995). Recent studies have extended TAM's application to contemporary digital tools, including OCR software, emphasizing its relevance to understanding students' behavioral intentions regarding new educational technologies (Abuhassna, H, et. al., 2023). Investigating OCR adoption through the TAM lens offers valuable insights into cognitive and affective factors driving students' awareness and utilization patterns. Examining students' awareness of OCR tools is critical because knowledge and familiarity often precede actual usage and influence perceived ease of use and usefulness. Studies have demonstrated that many undergraduate students utilize OCR-enabled applications to digitize textual information such as handwritten notes, scanned textbooks, and academic papers, substantially streamlining study practices (Hahn, Jim., 2024). However, awareness does not always guarantee optimal utilization, as barriers to usability, accessibility, and cost can impede effective adoption (Shaip, 2025). Thus, thoroughly exploring awareness and utilization through validated models like TAM can help identify impediments and facilitators of OCR technology use in education.

Moreover, the significance of OCR technology in accommodating students with diverse learning needs cannot be overstated. OCR tools support personalized learning by converting text into formats accessible for students with disabilities, including those with dyslexia or visual impairments, thereby promoting inclusivity in educational environments (Bartolo Ansaldi, 2022). As institutions strive to foster equitable learning spaces, understanding how students perceive OCR's utility and ease of use can inform the design and dissemination of assistive technologies. TAM's constructs thus provide a robust framework for capturing these perceptual variables influencing acceptance and sustained use among such student populations.

Furthermore, in the context of increasing digital transformation and online learning, OCR tools offer practical benefits by automating traditionally manual tasks such as note-taking, content searching, and document editing. These enhancements improve learning efficiency and support

Zenon A. Matos Jr. and Florence Jean B. Talirongan, "Examining Students' Awareness and Utilization of Optical Character Recognition Tools," *International Journal of Multidisciplinary Research and Publications (IJMRAP)*, Volume 7, Issue 12, pp. 611-617, 2025.

instructors and researchers in managing vast volumes of educational content (Saif Ali, 2024). With the ongoing digital shift accelerated by global events such as the COVID-19 pandemic, the relevance of examining students' engagement with OCR technology through the TAM model becomes even more pronounced, offering actionable insights for educators and technology developers aiming to optimize tool adoption.

II. MATERIALS AND METHODS

The study employs the Technology Acceptance Model (TAM) as the theoretical framework to examine students' awareness and utilization of optical character recognition tools. TAM is broadly recognized for its ability to understand client acknowledgment and utilization of innovation (An, M. et al., 2020). It centers on two essential constructs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which impact an individual's deliberate and genuine utilization of innovation.

A. Research Design

A quantitative research design was adopted to assess students' awareness and utilization of optical character recognition tools. This approach facilitates the collection of measurable data, enabling a systematic evaluation of TAM constructs in the context of OCR tools.

B. Population and Sampling

The study targeted higher education institution students in Zamboanga del Sur, as these contexts provide varied levels of technological integration. A stratified random sampling technique was used to ensure representation from diverse disciplines. A sample of 40 students was selected, with equal representation across subject areas.

C. Data Collection Instrument

A structured questionnaire was developed using the TAM framework to measure: Perceived Usefulness (PU): Items were designed to evaluate student perceptions of how optical character recognition tools enhance effectiveness and learning. Perceived Ease of Use (PEOU): Questions assessed the simplicity and ease of use of these tools in their tasks.
Behavioral Intention to Use (BI): Items captured students' intentions to integrate optical character recognition tools into their practice.
External Variables (EV): This section measures factors that indirectly influence perceptions and technology adoption.

The questionnaire included Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree), validated through alpha testing involving 14 students from higher education institutions. Feedback from the alpha testing was used to refine the instrument.

D. Data Collection Procedure

The survey was administered online and in person, ensuring accessibility for all participants. Data collection occurred, and reminders were sent to encourage participation. Informed consent was obtained, and anonymity was assured to protect participants' privacy.

E. Data Analysis

The collected data were analyzed using Structural Equation Modeling (SEM) to test the relationships among TAM constructs (PU, PEOU, BI, EV). Descriptive statistics were also computed to summarize students' levels of awareness and utilization of optical character recognition tools.

III. RESULTS AND DISCUSSIONS

Through the Technology Acceptance Model (TAM), the study looked at how aware and how well students use optical character recognition tools in higher education institutions. The data from 40 participants were analyzed using Structural Equation Modeling (SEM) and descriptive statistics.

TABLE 1: Respondents' Profile Distribution

Respondent Year Level	Frequency	Percentage
1st Year	5	12.50%
2nd Year	7	17.50%
3rd Year	10	25.00%
4th Year	18	45.00%
TOTAL	40	100.00%

As shown in Table 1, the respondents' profiles are distributed across various year levels within the BS in Information Technology. The breakdown helps understand the representation and focus areas within the group. The year level with the highest representation is 4th Year (n=18, 45%), 3rd Year (n=10, 20%), 2nd Year (n=7, 17.5%), and the 1st Year (n=5, 12.50%), with the least frequency representation.

A. Awareness and Utilization Levels

Descriptive analysis indicated that 100% of students knew optical character recognition (OCR) tools, such as Free and Open-Source OCR Tools, Online OCR Tools, and Paid Enterprise tools. However, only 80% reported regular usage, highlighting a gap between awareness and integration. This gap was more pronounced among students in the BS Information Technology program.

TABLE 2: Summary Results in terms of Perceived of Usefulness

Variables	Mean	Standard Deviation	Interpretation
The platform helps me accomplish tasks more quickly.	4.58	0.50	Very High
Using the platform improves the quality of my learning/teaching experience.	4.60	0.50	Very High
The platform enhances my productivity in learning/teaching.	4.63	0.49	Very High
The platform is useful for achieving my academic or professional goals.	4.65	0.48	Very High
I feel that the platform makes complex tasks easier to handle.	4.58	0.50	Very High
Overall Mean	**4.61**	**0.49**	**Very High**

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Table 2 shows that the platform is highly valued by its users, with an overall mean score of 4.61, categorized as "Very High." This suggests that users perceive the platform as extremely useful in various activities. Among the specific variables, the highest-rated aspect is the platform's usefulness in achieving academic or professional goals, with a mean of 4.65 and a relatively low standard deviation of 0.48, indicating substantial agreement among respondents.

Similarly, the platform is perceived as very effective in enhancing productivity, improving the quality of helping and accomplishing tasks more quickly, and making complex tasks more straightforward, with mean scores ranging from 4.58 to 4.63. The standard deviations, consistently between 0.48 and 0.50, show slight variation in responses, reflecting a high level of consensus. The platform is a valuable tool for productivity, learning, and achieving goals, with consistently positive user feedback.

TABLE 3: Summary Results in terms of Perceived Ease of Use

Variables	Mean	Standard Deviation	Interpretation
Learning to operate the platform is easy for me.	4.20	0.65	Very High
I find the platform's features are easy to understand and use.	4.23	0.48	Very High
The platform's features are easy to understand and use.	4.28	0.72	Very High
It is easy to navigate between different sections of the platform.	4.18	0.71	Very High
I can use the platform effectively without significant assistance.	4.15	0.74	Very High
Overall Mean	**4.21**	**0.66**	**Very High**

Table 3 shows that users find the stage profoundly usable, with a general mean score of 4.21, ordered as "Exceptionally High." Among the factors, the most highly evaluated viewpoint is the simplicity of understanding and utilizing the stage's highlights, with a mean score of 4.28 and a standard deviation of 0.72, reflecting somewhat more variety in reactions than the other factors. The simplicity of exploring various areas of the stage and working on it likewise got high appraisals, with mean scores of 4.18 and 4.20, respectively. Moreover, clients find the stage's elements straightforward and use, as reflected in the mean score of 4.23 and the least standard deviation of 0.48, demonstrating significant understanding. Lastly, clients accept that they can utilize the stage without huge help, with a mean of 4.15 and the best quality deviation of 0.74, showing somewhat more varied reactions. Overall, the platform is perceived as highly usable, with consistently positive ratings across all aspects, though minor variations in agreement are noted.

Table 4 shows the Behavioral Intention of Use results, indicating a strong positive inclination toward the platform, with an overall mean score of 4.40, categorized as "Very High." Among the variables, the highest-rated aspects are users' willingness to explore more features of the platform and their motivation to continue using it for academic or professional purposes, scoring 4.55, with low standard deviations of 0.50 and 0.60, respectively, reflecting strong agreement.

TABLE 4: Summary Results in terms of Behavioral Intention of Use

Variables	Mean	Standard Deviation	Interpretation
I intend to use the platform regularly in the future.	4.30	0.65	Very High
I am willing to explore more features of the platform.	4.55	0.50	Very High
I would recommend this platform to others.	4.58	0.50	Very High
I see myself depending on this platform for my learning/teaching needs.	4.03	0.62	Very High
I am motivated to continue using this platform for academic/professional purposes.	4.55	0.60	Very High
Overall Mean	**4.40**	**0.57**	**Very High**

Similarly, the intention to recommend the platform to others received a high mean score of 4.58, with a standard deviation of 0.50, indicating consistent responses. With a mean of 4.30 and a standard deviation of 0.65, the desire to use the platform frequently in the future received a high score. While slightly lower, depending on the platform for learning or teaching needs, it still received a "Very High" rating, with a mean score of 4.03 and a standard deviation of 0.62. Overall, the results suggest that users have a firm behavioral intention to use, explore, recommend, and rely on the platform for their academic and professional needs.

TABLE 5: Summary Results in terms of External Variables

Variables	Mean	Standard Deviation	Interpretation
I received adequate training to use the platform.	3.23	0.83	Very High
I feel supported by the technical support team when I face issues.	3.25	0.78	Very High
My peers/colleagues positively influence my decision to use the platform.	3.68	0.76	Very High
The platformâ€™s performance (speed, stability) meets my expectations.	4.05	0.64	Very High
The platform integrates well with other tools and systems I use.	4.03	0.48	Very High
Overall Mean	**3.65**	**0.70**	**Very High**

Table 5 presents the results for the External Variables, indicating a generally positive perception, with an overall mean score of 3.65, categorized as "Very High." Among the variables, the highest-rated aspects are the platform's performance (speed and stability) and its integration with other tools and systems, with mean scores of 4.05 and 4.03, respectively, and relatively low standard deviations (0.64 and 0.48), indicating consistent agreement among respondents. The influence of peers or colleagues on the decision to use the platform received a mean score of 3.68, with a standard deviation of 0.76, showing moderate agreement. Meanwhile, perceptions of receiving adequate training to use the platform and feeling supported by the technical team scored lower, with mean values of 3.23 and 3.25 and higher standard deviations (0.83 and 0.78), reflecting more significant response variability. Overall, while the platform's technical performance and integration are highly regarded, there is room for improvement in training and technical support to enhance the overall user experience.

TABLE 6: Summary Results

Variables	Mean	Standard Deviation	Interpretation
PERCEIVED OF USEFULNESS	4.58	0.5	Very High
PERCEIVED EASE OF USE	4.22	0.69	Very High
BEHAVIORAL INTENSION OF USE	4.39	0.57	Very High
EXTERNAL VARIABLES	3.65	0.72	Very High
TOTAL	**4.21**	**0.62**	**Very High**

Table 6 data reveals that all the variables measured demonstrate very high levels of perceived characteristics. The "Perceived Usefulness" means 4.58 with a standard deviation of 0.5, indicating a strong agreement that the subject's utility is highly regarded. Similarly, the "Perceived Ease of Use" shows a mean of 4.22 and a standard deviation of 0.69, reflecting a favorable view of how easy the subject is to use.
The "Behavioral Intention of Use" also scores high, with a mean of 4.39 and a standard deviation of 0.57, suggesting a substantial likelihood of continued use. "External Variables" have a mean of 3.65 and a standard deviation of 0.72, still rated highly, although slightly lower than the others. The total mean of 4.21 and a standard deviation of 0.62 indicate a consistently positive and very high perception across all variables.

B. Structural Equation Modeling

Table 7 shows the factor loadings of each latent variable using the confirmatory factor analysis. A factor loading is a number that indicates the degree to which an observable variable correlates with a latent variable. The table shows that four latent variables are measurable by five observable variables each. The result shows that all observable variables correlate directly to their latent variable, with all loadings being significant at a .05 alpha level.

Table 8 presents the reliability indices of the latent variables measured using five statements, each using Cronbach's alpha. The statistical measure used to assess the internal consistency or reliability of an assessment is Cronbach's alpha. The accepted Cronbach's alpha value is known to be greater than 0.7. Based on the table, there was an internal consistency of the items under each measured latent variable, as Cronbach's alpha is more significant than 0.7 for all variables.

Table 7: Factor Loading of Latent Variables

Latent	Observed	Estimate	p
External Variables	EV1	1	
	EV2	0.949	< .001
	EV3	0.559	< .001
	EV4	0.532	< .001
	EV5	0.833	< .001
Perceived Usefulness	PU1	1	
	PU2	1.16	< .001
	PU3	0.869	< .001
	PU4	1.101	< .001
	PU5	0.991	< .001
Perceived Ease of Use	PEOU1	1	
	PEOU2	0.935	< .001
	PEOU3	1.1	< .001
	PEOU4	1.121	< .001
	PEOU5	1.05	< .001
Behavioral Intention	BI1	1	
	BI2	1.148	< .001
	BI3	1.04	< .001
	BI4	0.904	< .001
	BI5	1.369	< .001

Note. * Significant at .05 alpha level

Table 8: Reliability Indices

Variable	Cronbach's Alpha
External Variable	0.804
Perceived Usefulness	0.885
Perceived Ease of Use	0.916
Behavioral Intention	0.736

Table 9: Model Fit Indices

Absolute Fit Indices		
	Chi-Square	183 (df=166; p = .175)
	Root Mean Square Error of Approximation (RMSEA)	.051 (p = .472)
	Goodness of Fit Index (GFI)	0.986
	Adjusted Goodness of Fit Index (AGFI)	0.981
Incremental Fit Indices		
	Comparative Fit Index (CFI)	0.999
	Normed Fit Index (NFI)	0.986

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Table 9 presents the model fit indices using the structural equation modeling. A model fit index in structural equation modeling (SEM) is a statistical value that measures how well a model fits data. It indicates how closely the model's predictions match the actual data. Absolute fit indices assess the degree to which a given a priori model fits the sample data (McDonald & Ho, 2002) and show which potential model has the best fit. The degree to which the suggested theory fits the data is best shown by these steps. Incremental fit indices, comparative (Miles & Shevlin, 2007), or relative fit indices (McDonald & Ho, 2002) do not use the chisquare in its raw form but compare the chisquare value to a baseline model. The null hypothesis for these models is that there is no correlation between any of the variables (McDonald & Ho, 2002). The Chi-square test value is the standard metric for assessing total model fit for absolute fit indices and "assesses the magnitude of discrepancy between the sample and fitted covariances matrices" (Hu and Bentler, 1999: 2). The ChiSquare statistic is sometimes referred to as a 'badness of fit' (Kline, 2005) or a 'lack of fit' (Mulaik et al, 1989) indicator, since a good model fit would yield an insignificant outcome at a 0.05 threshold (Barrett, 2007). Based on the table, the Chi-square value is 183 (df=166; p=.175). Here, the p-value is> .05. This means the model is acceptable. The RMSEA also informs us how well the model would fit the population's covariance matrix if the parameter estimates were unknown but chosen in the best possible way (Byrne, 1998). The upper bound should be below 0.08, while the lower limit should be near 0 in a well-fitting model. The RMSEA is often reported alongside it. The model also fits, as seen by the outcome. Likewise, the Goodness of fit statistic (GFI) and the change in the goodness of fit measurement (AGFI) ascertain the extent of difference that is represented by the assessed population covariance (Tabachnick & Fidell, 2007). The changes and covariances the model represents show how intently the model imitates the noticed covariance network (Diamantopoulos & Siguaw, 2000). It is mainly acknowledged that GFI and AGFI values of 0.90 or higher demonstrate well-fitting models.

The result shows that the model is fit. The NFI statistic compares the $\chi2$ value of the model to the $\chi2$ of the null model in order to evaluate the model for incremental fit indices. Bentler and Hu (1999) suggested that NFI $\geq$ 0.95 is the threshold. In a similar vein, the CFI compares the sample covariance matrix to this null model, which assumes that all latent variables are uncorrelated (null/independence model). A value of CFI $\geq$ 0.95 is presently recognized as indicative of a good fit (Hu & Bentler, 1999). Based on the results, both NFI and CFI are above 0.95, indicating an acceptable model.

Table 10 shows the path analysis, including the significance of the path coefficients. Based on the table, the path from External Variable to Perceived Ease of Use is significant ($p < .001$), while the path from External Variable to Perceived Usefulness is insignificant. This means that the External variable predicts the Perceived Ease of Use. Moreover, Perceived Usefulness has a significant path to Behavioral Intention, while Perceived Ease of Use does not have a significant path to Behavioral Intention. Perceived Usefulness is a predictor of Behavioral Intention. A diagram of the path analysis is shown below.

Table 10: *Path Coefficients of the Model*

Variables	Perceived Usefulness	Perceived Ease of Use	Behavioral Intention
External Variables	.208 (p = .083)	.458 (p < .001)	
Perceived Usefulness			.561 (p < .001)
Perceived Ease of Use			.036 (p = .704)

Note. * Significant at .05 alpha level.

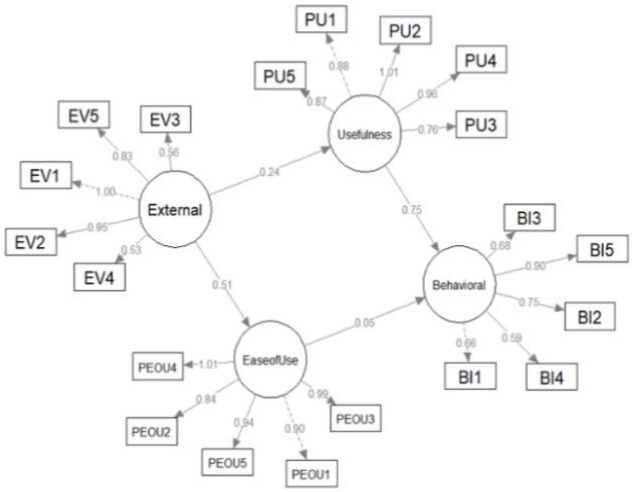

Figure 1: Path Analysis of the Model

C. Optical Character Recognition (OCR) Tools Accuracy Testing

The accuracy testing results of the Optical Character Recognition tool on handwritten and printed text highlight both its strong points and boundaries. The results also show that the tool's performance is less steady with handwritten input. While it performed very well in some handwritten tests, achieving over 90% accuracy in multiple cases, it also produced very low accuracy scores of as low as 14.29%. These instances suggest difficulty in processing poor or irregular handwriting, including cursive styles, overlapping characters, or noisy backgrounds. A six (6) test recorded accuracy has below 50%, highlighting that the tool struggles when the handwriting turns from well-ordered and readable forms. The optical character recognition tool (OCR) shows outstanding accuracy in reading printed text, reaching seamless scores in many tests, but its performance with handwritten text remains inconsistent. While it can handle clean, legible writing quite well, changeability in writing style and quality significantly affects its efficiency. To improve performance on handwritten participations, the use of preprocessing performances (e.g., contrast adjustment, noise reduction), enhanced OCR models trained on diverse writing datasets, and post-processing methods (like spell-checking and context-aware correction) are recommended. These enhancements could help bridge the gap between the tool's success with printed text and its limitations with handwritten material.

TABLE 11: Accuracy Testing Result

No. of Test	Total Characters	Correct Characters	Accuracy (%)
Test 1	13	10	76.92
Test 2	16	3	18.75
Test 3	23	7	30.43
Test 4	17	15	88.24
Test 5	18	18	100.00
Test 6	24	22	91.67
Test 7	18	15	83.33
Test 8	13	12	92.31
Test 9	20	19	95.00
Test 10	17	15	88.24
Test 11	18	18	100.00
Test 12	16	3	18.75
Test 13	17	15	88.24
Test 14	16	7	43.75
Test 15	14	12	85.71
Test 16	20	20	100.00
Test 17	17	12	70.59
Test 18	15	15	100.00
Test 19	20	20	100.00
Test 20	20	20	100.00
Test 21	22	15	68.18
Test 22	14	14	100.00
Test 23	13	10	76.92
Test 24	18	17	94.44
Test 25	14	2	14.29
Test 26	12	10	83.33
Test 27	17	15	88.24
Test 28	20	16	80.00
Test 29	22	22	100.00
Test 30	14	14	100.00

IV. Conclusion and Recommendation

The findings confirm the applicability of TAM in understanding students' adoption of optical character recognition (OCR) tools. Based on the descriptive statistics data presented in Table 6, it can be concluded that the perceived characteristics are very positive across all measures of 4.21 with the standard deviation of 0.62, with exceptionally high ratings in perceived usefulness, a mean of 4.58, perceived ease of use, a mean of 4.22, and behavioral intention of use, a mean of 4.39, and the external variables, a mean of 3.65. This demonstrates a consistently high acceptance and favorable perception of the students when it comes to optical character recognition tools awareness and utilization. Additionally, the accuracy rate across 30 tests was an overall average result of 79.24%, reflecting a moderately effective performance, especially in recognizing handwritten content, highlighting the struggles in processing poor or irregular handwriting, including cursive styles, overlapping characters, or noisy backgrounds. Notably, the tool reached 100% accuracy in 9 tests, many of which likely involved printed text. This is a strong indicator that the OCR tool system is exceedingly capable when dealing with clearly structured and printed characters. Printed text typically lacks the variability and irregularity of handwriting, making it easier for OCR algorithms to process and interpret precisely. The flawless results in these cases demonstrate the OCR tool's consistency and correctness in controlled, fine-text conditions. These discoveries emphasize the need to focus on preparing and bolstering to improve students' competency and confidence in utilizing OCR tools.

The study underscores the potential of OCR to support inclusive and efficient learning environments to improve training, integration, and policy support to foster greater student engagement with OCR technology. To enhance student awareness and utilization of OCR tools in academic environments, the institutions should conduct awareness campaigns, such as workshops, digital literacy classes, and orientation sessions, to introduce students to the benefits and functions of OCR tools for converting printed or handwritten text into editable digital formats. Promoting commonly available OCR tools can help students identify accessible solutions for their academic needs. Furthermore, integrating OCR tool usage into coursework and assignments can reinforce practical applications, while providing tutorials or demonstration videos through the institution's portals ensures continued support. Collaboration with library and IT staff can also ensure OCR-enabled devices and assistance are readily available. By actively involving faculty in recommending these tools and promoting their use for accessible learning, especially for students with disabilities, institutions can foster greater adoption and digital efficiency across diverse student groups.

Acknowledgment

They are deeply grateful to their family for providing them with support and encouragement. They sincerely appreciate your unwavering support and encouragement in participating in the advancement work at J.H. State of Cerilles. We appreciate the field experts' efficient participation in this review. Above all, thank and praise the almighty GOD for providing guidance and enthusiasm.

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