# AI Readiness and Prompting Literacy Among Multidisciplinary Special Needs Professionals

**Abdul Shakir V.V[1], Shirin Zeenath[2]**

**HOPE Qatar Centre for Persons with Disabilities**

**DOI: https://doi.org/10.47772/IJRISS.2026.102000015**

**Received: 15 October 2026; Accepted: 20 October 2026; Published: 19 October 2026**

## ABSTRACT

Artificial intelligence is transforming education and rehabilitation services by enabling new ways of assessing, documenting, communicating, and individualizing support, thereby improving the delivery of services to people with disabilities in special education settings.

This study aimed to investigate AI readiness and prompting literacy in a multidisciplinary sample of special needs professionals and determine any relationships between these skills. A quantitative cross-sectional design was used to collect data from 100 special needs professionals working within special education and rehabilitation services in Qatar from 6 different institutions. The sample included special educators, behaviour therapists, speech and language therapists, occupational therapists, psychologists, physiotherapists and allied professionals.

A 26 item self-report questionnaire was used to gather data. Descriptive statistics, correlation and multiple regression analysis were completed. There was a positive correlation between AI readiness and prompting literacy ($r = .643$, $p < .001$). The overall regression model revealed significant results for prediction of current AI use ($R^2 = .105$, $p = .005$). However, individual predictors were not significant once adjusted for. These findings demonstrate that the skills are related, however other factors may influence the use of AI within special needs.

Keywords: Artificial Intelligence, AI Readiness, Prompting Literacy, Multidisciplinary Practice

## INTRODUCTION

### Overview of Special Needs Care and Multidisciplinary Practice

Special Needs refers to the range of challenges- including physical, emotional, behavioral, or learning related difficulties that lead a person to need an extra or specialised support such as education or recreation (Merriam-Webster, 2026). The United Nations Convention on the Rights of the Child (UN, 1989) and the Convention on the Rights of Persons with Disabilities (UN, 2006), reflect a global commitment to ensuring that all students- including those with disabilities have access to quality education that supports their academic, social-emotional, and life-skills development.

### Artificial Intelligence in Special Education

Artificial Intelligence is the ability of computers or robots to do the tasks that generally only human intelligence could do (Copeland, 2026). The tasks include cognitive functions such as reasoning and decision making (Copeland, 2026). AI was also defined as the ability of non-human machines to perform human-like tasks- that include communication, interaction, logical reasoning and problem solving (Gil de Zúñiga et al., 2024). AI has affected many industries like healthcare, education, defense, and the commercial and military sectors (Golec et al., 2025).

Some of the areas where AI technologies have been used in special education include various applications aimed at enhancing the quality of education of children with special needs and overcoming specific learning challenges (Devadas, 2025).

The implications of using AI in relation to special needs differ depending on the professional field due to diverse foci, methods, interventions, assessments, and access (Harkins-Brown et al. 2025). There can be differences in readiness for the use of AI between professionals due to various factors like professional experience, training and availability of technology (Meadan et al., 2026).

### Prompt Engineering

The process of developing and improving textual instructions, or prompts, to direct large language models (LLMs) toward generating excellent, expectation-aligned output is known as prompt engineering (Sahoo et al., 2024). According to Zhang et al. (2024) even though AI systems are capable of generating answers to almost every subject, they fall short when it comes to creative or original thinking. Because of this, gaining the maximum advantage from AI highly depends on how well users can frame questions or instructions- users will receive more accurate output if the prompts are designed with utmost care (Zhang et al., 2024).

### Purpose of the Study

The study measures the level of AI readiness and prompting literacy in professionals, how it is being used at present, identifying the challenges present, and finding out the training needs required for the team to use AI effectively.

### Hypotheses

1. There is a significant positive relationship between AI Readiness and Prompting Literacy among multidisciplinary special needs professionals.

2. There is a significant positive relationship between AI Readiness and Current Use of AI among multidisciplinary special needs professionals.

3. There is a significant positive relationship between Prompting Literacy and Current Use of AI among multidisciplinary special needs professionals.

4. AI Readiness and Prompting Literacy significantly predict Current Use of AI among multidisciplinary special needs professionals.

5. There is a significant negative relationship between AI Readiness/Prompting Literacy and the Barriers professionals experience in using AI.

6. There is a significant relationship between the Barriers professionals' experience and their perceived Training Needs.

## METHODOLOGY

### Research Design

The design of the study is quantitative and cross-sectional. It is appropriate in this case because it provides for data collection at one point in time.

### Population and Sample

The study included 100 professionals working in special education and rehabilitation services in Qatar, drawn from six institutions. The professional distribution in the supplied response dataset was: Special Educator (n =

26), Occupational Therapist (n = 16), Behavior Therapist (n = 15), Physiotherapist (n = 11), Psychologist (n = 8), Special Educator / Psychologist (n = 6), Speech Therapist (n = 6), Assistant Special Educator (n = 4), Social worker (n = 3), Educator (n = 3), Mentor & Consultant (n = 1), Accountant & HR (n = 1).

**Sample Technique**

Purposive sampling was used to recruit participants working in special education, therapeutic, rehabilitation, or related support roles across six institutions in Qatar. Participants were personally approached and invited to participate in the study. A total of 100 responses were collected. The exact number of participants recruited from each institution was not recorded. To maintain confidentiality, the names of the institutions and participants were not disclosed. However, the sample size was not calculated using any pre-identified power calculations and therefore cannot be seen to have sufficient power to be representative. Due to the nature of the purposive sample, results may not be representative of all special needs professionals within Qatar.
Due to the absence of specific tools, a 26-item questionnaire was created. The survey used a 5-point Likert scale with the different sections being: AI Readiness (questions 1-8), Prompting Literacy (questions 9-13), Use of AI (questions 14-18), Barriers (questions 19-22) and Training Needs (questions 23-26). Training Needs focused on perceived needs to train in checking AI outputs; understanding bias and fabrication; understanding confidentiality; and professional accountability and organizational policies.

**Data Collection Procedure**

The 26-item questionnaire was developed specifically for this study and piloted to assess the clarity, relevance, and suitability of its items for multidisciplinary special needs professionals. However, no formal content validity index was calculated. The tool was also analysed for internal consistency using the Cronbach's alpha coefficient. The results showed that the AI Readiness and Prompting Literacy scales had low levels of internal consistency (.678 and .657 respectively). This is lower than the standard cut off point of .70 so caution should be taken when interpreting results from these scales.

**Data Analysis**

Pearson correlation coefficients were used to examine associations among AI Readiness, Prompting Literacy, Current Use of AI, Barriers, and Training Needs, consistent with the coefficients reported in Table 3.

**Results**

This chapter presents the findings of the study. Statistical significance was evaluated using an alpha level of .05.

**Reliability Analysis**

The internal consistency of the study scales was calculated using Cronbach's alpha (α). As shown in Table 1, the AI Readiness scale had a low level of internal consistency (α = .678). Similarly, the Prompting Literacy scale also had a low level of internal consistency (α = .657), therefore results should be interpreted with caution. The Current Use of AI scale had an acceptable level of internal consistency (α = .724). Both the Barriers measure (α = .853) and Training Needs measure (α = .911) showed high levels of internal consistency.

**Table 1 Reliability Statistics for the Study Scales**

| Scale | M | SD | Cronbach's α |
|---|---|---|---|
| AI Readiness | 3.69 | 0.534 | .678 |
| Prompting Literacy | 3.68 | 0.585 | .657 |
| Current Use of AI | 3.40 | 0.728 | .724 |
| Barriers | 2.80 | 1.05 | .853 |
| Training Needs | 3.54 | 1.08 | .911 |

Note. N = 100. M = mean; SD = standard deviation

**Descriptive Statistics**

Table 2 shows AI Readiness had a mean score of 3.69 (SD = 0.534), Prompting Literacy had a mean score of 3.68 (SD = 0.585). Current Use of AI had a mean of 3.40 (SD = 0.728), and Barriers had a mean score of 2.80 (SD = 1.05). The overall total score had a mean of 3.54 (SD = 1.08).

**Table 2 Descriptive Statistics of the Study Variables**

| Variable | N | M | SD |
|---|---|---|---|
| AI Readiness | 100 | 3.69 | 0.534 |
| Prompting Literacy | 100 | 3.68 | 0.585 |
| Current Use of AI | 100 | 3.40 | 0.728 |
| Barriers | 100 | 2.80 | 1.05 |
| Overall Total | 100 | 3.54 | 1.08 |

**Correlation Analysis**

Pearson correlation coefficients were calculated to examine the relationships among variables. The results are presented in Table 3.

AI Readiness was significantly and positively associated with Prompting Literacy, $r(98) = .643$, $p < .001$, indicating a moderate-to-strong positive relationship. AI Readiness was also positively associated with Current Use of AI, $r(98) = .312$, $p = .002$. In contrast, AI Readiness was negatively associated with Barriers, $r(98) = -.237$, $p = .018$. The relationship between AI Readiness and Training was not statistically significant, $r(98) = -.152$, $p = .131$.

Prompting Literacy was positively associated with Current Use of AI, $r(98) = .266$, $p = .007$, and negatively associated with Barriers, $r(98) = -.325$, $p < .001$. Its association with Training was also statistically significant and negative, $r(98) = -.233$, $p = .020$. Current Use of AI was not significantly related to Barriers, $r(98) = -.008$, $p = .938$, or Training, $r(98) = .141$, $p = .163$. Barriers were positively associated with Training, $r(98) = .401$, $p < .001$.

**Table 3 Pearson Correlations Among the Study Variables**

| Variable | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| AI Readiness | - | .643** | .312** | −.237* | −.152 |
| Prompting Literacy | .643** | - | .266** | −.325** | −.233* |
| Current Use of AI | .312** | .266** | - | −.008 | .141 |
| Barriers | −.237* | −.325** | −.008 | - | .401** |
| Training | −.152 | −.233* | .141 | .401** | - |

Note. N = 100. * $p < .05$. ** $p < .01$. Correlations are Pearson's r.

**Linear Regression Analysis**

The regression model was statistically significant, $R^2 = .105$, $F(2, 97) = 5.69$, $p = .005$. Thus, AI Readiness and Prompting Literacy together explained 10.5% of the variance in Current Use of AI.

As shown in Table 4, AI Readiness was not a statistically significant unique predictor of Current Use of AI after controlling for Prompting Literacy, B = 0.328, SE = 0.171, β = .240, t = 1.918, p = .058, 95% CI [-0.011, 0.667]. Prompting Literacy was also not a statistically significant unique predictor, B = 0.139, SE = 0.156, β = .112, t = 0.893, p = .374, 95% CI [−0.170, 0.449]. Although the overall regression model was significant, neither individual predictor reached the .05 significance threshold.

**Table 4 Multiple Linear Regression Predicting Current Use of AI**

| Predictor | B | SE B | β | t | p | 95% CI |
|---|---|---|---|---|---|---|
| Intercept | 1.678 | 0.517 | - | 3.248 | .002 | [0.653, 2.703] |
| AI Readiness | 0.328 | 0.171 | .240 | 1.918 | .058 | [−0.011, 0.667] |
| Prompting Literacy | 0.139 | 0.156 | .112 | 0.893 | .374 | [−0.170, 0.449] |

Note. N = 100. $R^2$ = .105, F(2, 97) = 5.69, p = .005. B = unstandardized coefficient; SE B = standard error; β = standardized coefficient; CI = confidence interval.

### Hypothesis Testing

H1: AI Readiness has a significant positive relationship with Prompting Literacy (r=.643, p<.001).

H2: AI Readiness and Current Use of AI indicate positive correlation (r=.312, p=.002).

H3: Prompting Literacy had a significant positive correlation with Current Use of AI (r = .266, p = .007).

H4: The overall regression model was statistically significant ($R^2$ = .105, p = .005). However, neither AI Readiness (p = .058) nor Prompting Literacy (p = .374) was a statistically significant unique predictor after adjustment for the other variable.

H5: AI Readiness and Prompting Literacy and Barriers are found to be negatively correlated with each other (r=-.237, p=.018) and (r=-.325, p<.001).

H6: Barriers and Training Needs are positively correlated (r=.401, p<.001).

## DISCUSSION

### Overview of Major Findings

The study has one hundred responses. Overall, the results show that participants reported reasonably high levels of AI readiness and prompting literacy with mean scores of 3.69 and 3.68 respectively on the five-point measures. The mean score of the current use of AI was 3.40. The mean score of the obstacles of use of AI was 2.80. Correlation analysis revealed a statistically significant positive link between AI readiness and prompting literacy, r(98) =.643, p <.001. AI preparedness was also strongly correlated with present use of AI, r(98) =.312, p =.002. Overall the multiple regression model was statistically significant, R2 = .105, F(2, 97) = 5.69, p = .005. However, neither AI readiness nor prompting literacy was a statistically significant unique predictor when both variables were input concurrently.

### Relationship Between AI Readiness & Prompting Literacy

There was a large and statistically significant positive link between AI readiness and prompting literacy, r(98) = .643, p < .001. This result suggests that participants with higher degrees of AI preparedness also tended to report higher levels of prompting literacy. The amplitude of the correlation indicates that these constructs are substantively related in the study population.

This finding supports the idea that effectively using generative AI is not only a matter of knowing that AI tools exist. Those who are more comfortable with AI, and hence more ready, may be better positioned to craft clear cues, to refine outputs and to employ AI more strategically.

### Current Use of AI

The average score for current usage of AI was 3.40 (SD = 0.728), which is lower than the averages for AI readiness and prompting literacy. And that's a crucial distinction, since being comfortable or ready to utilise AI doesn't necessarily translate to frequent or widespread use in the workplace.

AI readiness and current AI use were positively correlated, r(98) = .312, p =.002, such that higher AI readiness was associated with higher current use. Present AI use was also positively correlated with literacy promotion (r (98) =.266, p =.007). These associations suggest that practical experience and confidence might help promote the adoption of AI. However, the associations are not strong enough to show that preparedness or prompting literacy alone explains AI use.

### Barriers

Barriers mean score was 2.80 (SD = 1.05) and demonstrated larger variation across participants' views of barriers than was reported for AI readiness or prompting literacy. The greater standard deviation indicates respondents did not experience barriers in the same way or to the same level.

Barriers were adversely associated with AI readiness, r(98) = −.237, p = .018 and prompting literacy, r(98) = −.325, p <.001. These results show that professionals reporting more hurdles also reported worse readiness and prompting literacy. Training Needs were assessed using four questions (23-26) relating to verification, bias, confidentiality and professional responsibility. There is a positive relationship between barriers and training needs (r = .401, p < .001) indicating that individuals who experience higher levels of barriers also felt they had higher training needs. This does not imply that training would reduce barriers.

### Training

Training was significantly negatively correlated with prompting literacy, r(98) = −.233, p = .020, and significantly positively correlated with obstacles, r(98) = .401, p < .001. Training was not significantly correlated with AI readiness, r(98) = −.152, p = .131, or current AI use, r(98) = .141, p = .163. The model explains 10.5% of the variation in current use of AI technologies. Other factors such as professional experience, availability of resources within their institution, access to AI technologies, and policies will have an influence on how they use AI technologies. This model does not look at these factors as predictors. Also, since this was a cross-sectional study, the results cannot be seen as causal.

### Regression Findings

A multiple regression was used to see if AI readiness and prompting literacy predicted current use of AI. The total model was significant, R2 = .105, F(2, 97) = 5.69, p = .005, showing that the two predictors accounted for 10.5% of the variance in current AI use.

## CONCLUSION

### Summary of Findings

The results show that the professionals had a relatively high level of AI readiness (M = 3.69; SD = 0.534). This indicates that the majority of employees have some experience with AI but to varying degrees. It was also discovered that the professionals had a relatively high level of prompting skills (M = 3.68; SD = 0.585). A strong and significant relationship was found between AI competence and prompting skills (r = .643; p < .001). Both AI competence and prompting skills were also found to have significant relationships with current AI usage. The multiple regression analysis showed thatWhilst the overall model was statistically significant (R 2 = .105; p =

.005), when looking at individual variables AI readiness was not significant (p = .058) nor was prompting literacy (p = .374). This suggests that whilst general knowledge of AI and prompting skills are associated with how much is put into practice, they are entangled. Other factors which aren't explained by the variables have an impact on the actual situation. It was found that the professionals had relatively few barriers when using AI (M = 2.80; SD = 1.05). However, there was a larger variety of responses here compared to the strengths. From these results we can see that barriers are a strong negative factor. Those with a high level of competence will find it easier to use AI within their role. Training needs was found to have a significant positive correlation with barriers (r = .401; p < .001). It also had an inverse correlation with prompting literacy (r = -.233; p = .020). It appears those who are less skilled in prompting and encounter more barriers are likely to identify a training need.

**Recommendations: Training and Skills Development Plan**

Any use of AI in a professional context would require sensitive client data to be protected, institutional data protection policies adhered to and human professional involvement maintained. The recommendations generated by the AI may not always be accurate, could be biased and may not be appropriate for the individual learner so they should be checked. The sample used was purposefully selected and therefore is not representative of the population. There was no formal sample size calculation carried out and the names of the institutions were not disclosed to maintain confidentiality. Within the questionnaire, there were two subscales included which had low levels of internal consistency.

The findings of the research lead us to put forward a number of skills development and training suggestions for organizations working in the sphere of special education that plan to prepare their employees for the use of AI.

**Practical Implications**

The research indicates that while professionals in a special needs environment seem to accept and understand AI, actual implementation is not keeping up with readiness and knowledge. This shows that there is a major difference between knowledge and action – a difference that can be bridged through the provision of training at the organizational level.

**Limitations**

There are few limitations of the current study as discussed in Chapter 5. First and foremost, the use of a cross-sectional design limits the ability to provide causal conclusions about the relationships between AI readiness, prompting literacy and the extent of usage. The data collected in this study are based on self-reports presenting the issue of social desirability and self-assessment bias.

**Directions for Future Research**

- The future research may utilize longitudinal or pre-test-post-test designs to evaluate whether training programs can improve prompting literacy, thus leading to the improvement of AI utilization over some time.
- The research may employ larger samples to improve the generalization findings and allow for appropriate comparisons between disciplines, experience, and institutional backgrounds.
- Future research may incorporate organization-based variables to eliminate the variance unexplained in the regression model of this study.

## REFERENCES

1. Copeland, B. J. (2026, June 11). Artificial intelligence. *Encyclopaedia Britannica*. https://www.britannica.com/technology/artificial-intelligence
2. Devadas, R. S. (2025). AI augmented education for children with special needs: A scholarly perspective. World Journal of Advanced Engineering Technology and Sciences, 15(3), 2000–2008. https://doi.org/10.30574/wjaets.2025.15.3.1125

3. Gil de Zúñiga, H., Goyanes, M., & Durotoye, T. (2024). A scholarly definition of artificial intelligence (AI): Advancing AI as a conceptual framework in communication research. Political Communication, 41(2), 317–334. https://doi.org/10.1080/10584609.2023.2290497
4. Golec, M., Hatay, E. S., Gill, S. S., & Buyya, R. (2025). Artificial intelligence (AI): Foundations, trends and future directions. Telematics and Informatics Reports, 20, Article 100265. https://doi.org/10.1016/j.teler.2025.100265
5. Merriam-Webster. (2026, April 2). Special needs. In Merriam-Webster.com dictionary. Retrieved July 18, 2026, from https://www.merriam-webster.com/dictionary/special%20needs
6. Sahoo, P., Singh, A. K., Saha, S., Jain, V., Mondal, S. S., & Chadha, A. (2024). A systematic survey of prompt engineering in large language models: Techniques and applications. arXiv. https://doi.org/10.48550/arXiv.2402.07927
7. United Nations. (1989). Convention on the Rights of the Child. https://www.ohchr.org/en/instruments-mechanisms/instruments/convention-rights-child
8. United Nations. (2006). Convention on the Rights of Persons with Disabilities. https://www.ohchr.org/en/instruments-mechanisms/instruments/convention-rights-persons-disabilities
9. Zhang, K., Zhou, F., Wu, L., Xie, N., & He, Z. (2024). Semantic understanding and prompt engineering for large-scale traffic data imputation. Information Fusion, 102, Article 102038. https://doi.org/10.1016/j.inffus.2023.102038