Readiness of Accounting Students in Riau Province to Artificial Intelligence in Accounting

Donal Devi Amdanata^{1*}, Burhan², Agus Seswandi³, Aulia Rani Annisava⁴ {donaldev.mec@gmail.com^{1*}, burhan@unilak.ac.id², agusseswandi@unilak.ac.id³, auliarani.dda@gmail.com⁴}

^{1,2,3}Universitas Lancang Kuning, Pekanbaru, Indonesia ⁴Universitas Islam Negeri Sultan Syarif Kasim Riau, Pekanbaru, Indonesia

Abstract. The purpose of this study is to determine how prepared accounting students are to embrace artificial intelligence (AI) in the field. This research employs a quantitative approach with a Google Forms-distributed questionnaire. A sample of 152 accounting students from Indonesian institutions in the Riau Province participated in this study. The data for this investigation are analyzed using the PLS-SEM method. The study's findings are in line with other research, which found a strong correlation between technical preparedness and AI technology. As mediating variables, this study included supporters of AI technology in the form of technological tools and human resources. The findings indicate a strong positive correlation between AI technology and its support factors. It does not, however, prove that there is a meaningful link in the indirect relationship.

Keywords: Artificial Intelligence; Accounting; Technology

1 Introduction

The readiness of accounting students to face technological advances, especially Artificial Intelligence (AI) technology, is strongly influenced by various factors, one of which is the adjustment of teaching methods and curriculum to ensure that accounting graduates are equipped with the skills needed for a changing industry [1]. Tavares et al.(2023) expressed their expectations for the accounting profession in the upcoming 5.0 era. He suggested that educational institutions and other organizations interact in the change process, creating synergies to ensure the successful retraining of strategic resources in organizations and society to promote a sustainable 5.0 Society.

The results of research conducted by Vărzaru (2022) show that the application of artificial intelligence solutions in managerial accounting offers many options for managers through innovation and streamlining processes, increasing the use of accounting information, and is relatively easy to use, given the high degree of automation and customization. The future of the accounting and auditing profession relies heavily on artificial intelligence technologies as these technologies provide the means to perform tasks more effectively and efficiently [4]. AI has significantly improved operations, reporting, and decision-making processes in accounting and auditing, among other fields. Key roles and tasks will continue to exist in the future; however, some will not be performed by humans but by AI-based technologies [5].

A study conducted in Portugal found that the massive spread of digital technology has changed the needs of the industry [6]. In the same study, Gonçalves et al. (2022) revealed that

AI is one of the technologies of interest for development. However, AI research and the application of AI in life are still in their early stages [7].

A study conducted by Amdanata et al. (2023) found that technological readiness did not actually affect students' knowledge of AI in accounting. This means that even though accounting students are aware of the existence of AI technology in accounting, their knowledge of the technology is minimal because students need to interact with it. In addition, Dai et al. (2020) revealed that AI literacy cannot predict AI readiness. The effect of AI literacy is mediated by self-confidence and students' perception of AI relevance.

However, Amdanata et al. (2023) found that knowledge of the convenience of AI technology in accounting has a real influence on the technology. This means that if students know the convenience or advantages of AI technology, then students will become aware of this technology. In line with this research, in the findings of Chergarova et al. (2023), most participants used AI tools out of curiosity.

Continuing the research of Amdanata et al. (2023), which aims to determine the perceptions of accounting students towards AI technology in accounting, this study will try to see the readiness of accounting students towards AI technology in accounting.

2 Literature Review

AI is one of the latest studies of interest related to intelligent thoughts that can be used to calculate [11]. The presence of AI technology in the era of the industrial revolution 4.0 further complements the convenience of automation and control, improves the transaction documentation process, and makes financial reports more efficient [12].

In its development, more and more fields of science are developing and using AI technology, such as science, social, health, psychology, law, education and others. Not only that, AI technology is also developing in various industries, such as automotive, energy, manufacturing, finance and so on. The use of AI in various fields of science and life is increasingly in demand because AI provides conveniences such as solving problems and even helping to make decisions.

This rapid development of AI technology, in particular, attracts accounting researchers to apply AI technology in accounting. The research results of Leitner-Hanetseder et al. (2021) show that the tasks and talent for existing professional jobs in the context of accounting will undergo significant changes in the next ten years due to digital technology; some jobs in accounting will not be conducted by humans but by AI.

Accounting is classified as an information system, and combining accounting with information technology will further expand the ability of accounting to improve productivity [13]. Accountants must be able to improve their performance in company operations. Accounting practices are not the only ones to benefit from information technology; societies, students, and accounting systems have been effectively affected by the power of digital systems, knowledge of information systems and technologies, and applications in accounting education [13].

Abukhader (2020) said that the opportunity for the entry of information technology into accounting practice is two-thirds of the series of tasks and obligations performed by accountants and auditors. This finding shows that the marriage between accounting and information technology is not impossible.

The demand for adding AI learning in accounting has been emerging for a long time. Baldwin-Morgan (1995) has suggested universities start integrating AI into the accounting curriculum. However, there is a challenge that AI technology is not easily taught to students outside the computer or engineering fields [16].

Jöhnk et al. (2021) offer five categories of AI readiness factors and illustrative indicators that can be acted upon, namely strategic alignment, resources, knowledge, culture, and data. The resources indicator has three influencing factors: financial budget, personnel, and IT infrastructure. Nouraldeen (2023) revealed that accounting educators in universities should try to increase the adoption of AI by students before releasing them into the workforce by adjusting the curriculum of accounting programs so that students are ready to use AI systems. In addition, they should prepare students to have good technology skills through AI software training.

It is very appropriate if universities can implement Merdeka Belajar programs that allow students majoring in accounting to study in computer majors and vice versa so that graduates of both fields can adjust to industry needs [18].

3 Methodology

This research was conducted at several universities in Riau Province. The object of this research is students majoring in accounting. The universities used as research locations are Universitas Riau (UNRI), UIN Sultan Syarif Kasim (UIN Suska), Universitas Lancang Kuning (Unilak), Universitas Muhammadiyah Riau (UMRI), Universitas Pasir Pangaraian (UPP).

The questionnaire was distributed to each selected university via a Google form. The target questionnaire distributed was 350, but the returned questionnaires were 152. This research uses quantitative methods. The data used is acquired from distributing questionnaires to the object of study.

The variables studied are Technology Readiness (KT), Knowledge and Usefulness of Technology (PKEG), Knowledge and Ease of Technology (PKEM), Supporting AI Technology (PTAI), and Knowledge of Artificial Intelligence (AI) Technology. The data obtained will be analyzed using SmartPLS 3 software.

4 Result and Discussion

In order to assess the presented hypotheses, Partial Least Square (PLS) employs a two-stage analytical technique [19], [20]. The suggested model is measured and its validity and reliability are examined in the first step. Subsequently, presenting empirical data to bolster the theoretical and speculative models for structural model evaluation constitutes the second phase. Structural equation modeling with PLS methods, which provides a flexible statistical approach employing rigorous and robust processes [21], was used to evaluate hypotheses [22].

The next section presents the measurement model's primary findings. Since the Variance Inflation Factor (VIF) values of all the models are less than 10, multicollinearity is not an issue [23]. The reliability, convergent validity, and discriminant validity of the measurement models were evaluated as a necessary precondition for obtaining valid results.

The scales' convergent validity and reliability were confirmed by applying the following three Fornell & Larcker (1981) criteria: In order to establish reliability, each construct's Composite Reliability (CR) and Cronbach Alpha should both surpass 0.7 [13]; additionally,

each item's reliability for each standardized factor loading should be significant and above 0.7 [23]; Third, each construct's Average Variance Extracted (AVE) should be greater than the variance resulting from measurement error (i.e., the AVE should exceed 0.50) in order to ensure convergent validity. All latent variable measures in this instance are reflective. Table 3 shows that all of the loading factors are higher than the suggested threshold of 0.7.

The data set's reliability was confirmed by the construct Cronbach Alpha, which ranged from 0.700 to 0.942, and the composite reliability, which ranged from 0.868 to 0.954, both exceeding the benchmark of 0.7. If the latent variables' AVE is retrieved, convergent validity can be evaluated. The AVE values of all latent variables, which range from 0.651 to 0.882, are more than the complementary value of 0.50. Table 1 presents the measuring model.

The data processing results show that this research is consistent with previous research [8]. In Amdanata et al.(2023) research, the research respondents were only conducted in one university, while in this study, the research respondents involved respondents from more than six universities. This study also added AI technology support variables as mediating variables. However, these additional variables did not significantly affect AI technology knowledge.



Figure 1. Conceptual Framework

| l'able i | Measurement | i Model | Resul | ts |
|----------|---------------------------------|----------------|---------|-----------|
| | | / | | · · · · · |
| | • N/I/A/16/117/ATT1/AT11 | • 11/1/1/1/1/1 | | |
| | | | 1 | |
| 1 11/10 | | | 1.0.000 | |

| Construct | Items | Factor Loading (tb) (>0,6) | Cronbach's Alfa (>0,6) | CR (>0,7) | AVE (>0,05) |
|---------------------------|-------|----------------------------------|---------------------------|--------------|----------------|
| Technology Readiness (KT) | | | 0,700 | 0,868 | 0,767 |
| | KT1 | 0,904 | | | |
| | KT2 | 0,846 | | | |
| Knowledge and Usefulness | | | 0,940 | 0,953 | 0,771 |
| of Technology (PKEG) | PKEG1 | 0,879 | | | |
| | PKEG2 | 0,876 | | | |
| | PKEG3 | 0,893 | | | |
| | PKEG4 | 0,920 | | | |
| | PKEG5 | 0,873 | | | |
| | PKEG6 | 0,824 | | | |
| | | | 0,942 | 0,954 | 0,775 |

| Knowledge and Ease of | PKEM1 | 0,844 | | | |
|--------------------------|-------|-------|-------|-------|-------|
| Technology (PKEM) | PKEM2 | 0,874 | | | |
| | PKEM3 | 0,904 | | | |
| | PKEM4 | 0,886 | | | |
| | PKEM5 | 0,864 | | | |
| | PKEM6 | 0,908 | | | |
| AI Technology Supporters | | | 0,893 | 0,918 | 0,651 |
| (PTAI) | PTAI1 | 0,765 | | | |
| | PTAI2 | 0,772 | | | |
| | PTAI3 | 0,812 | | | |
| | PTAI4 | 0,853 | | | |
| | PTAI5 | 0,854 | | | |
| | PTAI6 | 0,780 | | | |
| AI Technology Knowledge | | | 0,867 | 0,937 | 0,882 |
| (AI) | AI1 | 0,938 | | | |
| | AI2 | 0,940 | | | |

Table 2. Result of Hypothesis Testing

| | Path Coefficient | P Values | Result |
|--|------------------|----------|---------------|
| KT → AI | 0,194 | 0,036 | Supported |
| KT PKEG | 0,613 | 0,000 | Supported |
| $KT \rightarrow PKEM$ | 0,138 | 0,258 | Not Supported |
| $\mathrm{KT} \twoheadrightarrow \mathrm{PTAI}$ | 0,098 | 0,426 | Not Supported |
| PKEG \rightarrow AI | 0,265 | 0,015 | Supported |
| PKEG \rightarrow PKEM | 0,604 | 0,000 | Supported |
| PKEG \rightarrow PTAI | 0,022 | 0,873 | Not Supported |
| PKEM \rightarrow AI | 0,243 | 0,064 | Not Supported |
| PKEM \rightarrow PTAI | 0,324 | 0,012 | Supported |
| $\mathrm{PTAI} \mathrm{AI}$ | 0,203 | 0,009 | Supported |

Table 3. Specific Indirect Effects

| Path | P-values | t-values | Result |
|---|----------|----------|-------------|
| $\text{KT} \rightarrow \text{PKEG} \rightarrow \text{AI}$ | 0,020 | 2,337 | Significant |
| $KT \rightarrow PKEG \rightarrow PKEM$ | 0,000 | 6,314 | Significant |
| PKEG \rightarrow PKEM \rightarrow PTAI | 0,027 | 2,214 | Significant |
| $KT \rightarrow PKEG \rightarrow PKEM \rightarrow PTAI$ | 0,030 | 2,170 | Significant |

The structural model and hypotheses were estimated primarily by analyzing the measured variance (\mathbb{R}^2) with antecedent constructs. Based on Cohen's (1988) proposed 0.02, 0.13, and 0.26 as small, medium, and significant variances, respectively; second, the significance of path coefficients and total effects obtained using the bootstrap procedure and calculating t values and p values. Table 4 shows the relationships between the research variables. Almost all relationships show a relationship that is consistent with the research of Amdanata et al. (2023). An interesting finding is the significant relationship between independent variables and mediating variables on AI technology knowledge, all of which show a significant relationship,

except for the PKEM variable. This finding is consistent with the results of specific indirect effects, which show no significant relationship between PKEM and PTAI. This means that the knowledge of the ease of AI technology only affects students of AI technology.

Based on Table 2 and Table 3, in the results of processing specific indirect effect data, only a few relationships have a significant effect. However, none of them affect the variable Use of AI Technology. This shows that the Use of AI Technology does not require a mediating relationship but a direct relationship with the research variables, except for the Ease of Technology Knowledge variable.

5 Conclusion

Research on AI technology, especially those related to accounting, is still too little studied by researchers in Indonesia. Some researchers who try to be consistent in this field are Amdanata et al. (2023) who are still in the early stages of AI research in accounting; Tandiono (2023) who examines in terms of literature review; and Sudaryanto et al. (2023) who examined the relationship between several variables towards AI technology in accounting.

Based on this research, some variables that have been studied several times [17], [26], [27] should not need to be re-examined because they have shown consistent results. As a recommendation for further research in AI in accounting, the supporting indicators for teaching AI in accounting in universities should be examined.

References

- R. Tandiono, "The Impact of Artificial Intelligence on Accounting Education: A Review of Literature," in *E3S Web of Conferences*, 2023, vol. 426, pp. 1–7. doi: 10.1051/e3sconf/202342602016.
- [2] M. C. Tavares, G. Azevedo, R. P. Marques, and M. A. Bastos, "Challenges of education in the accounting profession in the Era 5.0: A systematic review," *Cogent Bus. Manag.*, vol. 10, no. 2, pp. 0–30, 2023, doi: 10.1080/23311975.2023.2220198.
- [3] A. A. Vărzaru, "Assessing Artificial Intelligence Technology Acceptance in Managerial Accounting," *Electron.*, vol. 11, no. 14, pp. 1–13, 2022, doi: 10.3390/electronics11142256.
- [4] S. M. Ali, Z. J. Hasan, A. Hamdan, and M. Al-Mekhlafi, "Artificial Intelligence (AI) in the Education of Accounting and Auditing Profession," *Lect. Notes Networks Syst.*, vol. 620 LNNS, pp. 613–621, 2023, doi: 10.1007/978-3-031-26953-0_56.
- [5] S. Leitner-Hanetseder, O. M. Lehner, C. Eisl, and C. Forstenlechner, "A Profession in Transition: Actors, Tasks and Roles in AI-based Accounting," J. Appl. Account. Res., vol. 22, no. 3, pp. 539– 556, 2021, doi: 10.1108/JAAR-10-2020-0201.
- [6] M. J. A. Gonçalves, A. C. F. da Silva, and C. G. Ferreira, "The Future of Accounting: How Will Digital Transformation Impact the Sector?," *Informatics*, vol. 9, no. 1, pp. 1–17, 2022, doi: 10.3390/informatics9010019.
- [7] J. Jöhnk, M. Weißert, and K. Wyrtki, "Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors," *Bus. Inf. Syst. Eng.*, vol. 63, no. 1, pp. 5–20, 2021, doi: 10.1007/s12599-020-00676-7.
- [8] D. D. Amdanata, Burhan, A. Seswandi, and A. R. Annisava, "Siapkah Mahasiswa Akuntansi Menghadapi Artificial Intelligence Dalam Akuntansi ?," J. Akunt. Kompetif, vol. 6, no. 1, pp. 163– 174, 2023.
- [9] Y. Dai, C. S. Chai, P. Y. Lin, M. S. Y. Jong, Y. Guo, and J. Qin, "Promoting students' well-being

by developing their readiness for the artificial intelligence age," *Sustain.*, vol. 12, no. 16, pp. 1–15, 2020, doi: 10.3390/su12166597.

- [10] V. Chergarova, M. Tomeo, L. Provost, G. De la Peña, A. Ulloa, and D. Miranda, "Case study: exploring the role of current and potential usage of generative artificial intelligence tools in higher education," *Issues Inf. Syst.*, vol. 24, no. 2, pp. 282–292, 2023, doi: 10.48009/2_iis_2023_125.
- [11] S. Singh and S. Singh, "Artificial Intelligence," Int. J. Comput. Appl., vol. 6, no. 6, pp. 21–23, 2010.
- [12] A. Muawanah, D. Adawiyah, I. Maisarah, M. R. A. Ali, and N. P. E. Widiastuti, "Perilaku Auditor Menyikapi Munculnya Artificial Intelligence dalam Proses Audit," *J. Publ. Ekon. dan Akunt.*, vol. 2, no. 1, pp. 52–60, 2022.
- [13] S. N. Kovalenko, N. A. Kalutskaya, A. I. Bolvachev, N. A. Prodanova, L. V. Sotnikova, and O. P. Shevchenko, "Artificial Intelligence in The Accounting Profession," *Laplage em Rev.*, vol. 7, pp. 378–383, 2021, doi: 10.24115/s2446-622020217extra-b939p.384-395.
- [14] S. M. Abukhader, "Extent of artificial intelligence into accounting and auditing work An analytical attempt of job and duties," *Int. J. Bus. Process Integr. Manag.*, vol. 10, no. 2, pp. 125– 136, 2020, doi: 10.1504/ijbpim.2020.117165.
- [15] A. A. Baldwin-Morgan, "Integrating artificial intelligence into the accounting curriculum," *Account. Educ.*, vol. 4, no. 3, pp. 217–229, 1995, doi: 10.1080/09639289500000026.
- [16] J. J. Xu and T. Babaian, "Artificial Intelligence in Business Curriculum: The Pedagogy and Learning Outcomes," Int. J. Manag. Educ., vol. 19, no. 3, 2021, doi: 10.1016/j.ijme.2021.100550.
- [17] R. M. Nouraldeen, "The impact of technology readiness and use perceptions on students' adoption of artificial intelligence: the moderating role of gender," *Dev. Learn. Organ.*, vol. 37, no. 3, pp. 7– 10, 2023, doi: 10.1108/DLO-07-2022-0133.
- [18] Direktorat Jenderal Pendidikan Tinggi Kementerian Pendidikan dan Kebudayaan, Buku Panduan Merdeka Belajar-Kampus Merdeka. 2020.
- [19] J. C. Anderson and D. W. Gerbing, "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach," *Psychol. Bull.*, vol. 103, no. 3, pp. 411–423, 1988, doi: 10.1037/0033-2909.103.3.411.
- [20] J. F. Hair, R. E. Anderson, R. L. Tatham, and W. C. Black, *Multivariate Data Analysis: A Global Perspective*, 7 Pearson. 2010.
- [21] H. Wold, "Model Construction and Evaluation When Theoretical Knowledge Is Scarce. Theory and Application of Partial Least Squares," in *Evaluation of Econometric Models*, 1980, pp. 47–74. doi: 978-0-12-416550-2.
- [22] W. W. Chin, "PLS-Graph, Version 3.00 (Build 1130), University of Houston," Houston. TX, 2003.
- [23] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis: Pearson New International Edition*, 7th ed. Essex, England: Pearson Education Limited, 2014.
- [24] C. Fornell and D. F. Larcker, "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," J. Mark. Res., vol. 18, no. 1, pp. 39–50, 1981, doi: Article.
- [25] J. Cohen, "Statistical power analysis for the behavioral sciences. 1988, Hillsdale, NJ: L," Lawrence Earlbaum Assoc., vol. 2, 1988.
- [26] M. R. Sudaryanto, M. A. Hendrawan, and T. Andrian, "The Effect of Technology Readiness, Digital Competence, Perceived Usefulness, and Ease of Use on Accounting Students Artificial Intelligence Technology Adoption," in *E3S Web of Conferences*, 2023. doi: 10.1051/e3sconf/202338804055.
- [27] H. Damerji and A. Salimi, "Mediating Effect of Use Perceptions on Technology Readiness and Adoption of Artificial Intelligence in Accounting," *Account. Educ.*, vol. 30, no. 2, pp. 107–130, 2021, doi: 10.1080/09639284.2021.1872035.