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The Bane of AI in Teaching: Innovation Resistance in Higher Education Instructional Design & Delivery

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Abstract: Technology integration is becoming a norm in the education industry, with AI gaining increasing popularity to help improve academic productivity and efficiency. This study proposes to take a different perspective of technology adoption by examining resistance to the use of AI by higher education teachers, despite the tools' and applications' known advantages. The study involves the use of an extended innovation resistance theory (IRT) to achieve the research objective of identifying different functional and psychological barriers, as well as technological and self-inefficacy barriers to AI adoption in instructional design. Moreover, the extent of innovation resistance will be further determined based on the use of AI technologies in various instructional design phases based on the ADDIE Model and expected teaching practitioners' skills and competencies based on the SFIA 8 standards. A mixed-method approach will be used to collect and analyze both quantitative data about AI utilization and qualitative data to determine the barriers, including why such exist. The output of this research aims to help identify opportunities for enhancing teacher competency in technology integration in higher education, AI advocacy, and policy development on the responsible and ethical use of AI in instructional design.

Keywords: AI in education, innovation resistance, technology adoption, instructional design, higher education

1. Introduction

Education 5.0 has brought about the integration of advanced technologies in the learning and teaching environment. Following the trends in the Fifth Industrial Revolution (5IR), it allows for enhanced, student-centric academic outputs and processes through human-artificial intelligence (AI) collaboration, internet of things (IoT), extended realities, and other smart technologies (Ahmad et al, 2023). This entails incorporating technology into the curriculum and leveraging technology to enhance the learning experience. Unfortunately, the Philippines is still a laggard in adoption as evidenced in its technological advancement, educational facilities, and strategies towards becoming Education 4.0 (Pangandaman, 2019). While there are numerous contemporary studies on AI in Education (AIEd), particularly on the students' use of generative AI and personalized learning assistants, research on the teachers' perspective on AI technology adoption remain to be scarce. This study aims to examine the factors that affect the use of AI tools for instructional design in higher education, including generative AI, chatbots, and AI-enabled learning management systems (LMS).

2. Literature Review

2.1 AI & Technology Adoption in Higher Education

Technology adoption in higher education is not a new research topic, but has recently gained traction since the use of online distance learning and emergency remote teaching technologies necessitated by the COVID-19 pandemic. Currently, technology adoption has become popular due to AIEd and the use of different emerging AI technologies, such as generative AI, chatbots, personal learning assistants, AI-enabled learning management systems (LMS), and other AI systems using analytics. Similar to past studies on technology adoption in other fields, systematic literature reviews (SLRs) indicate that student, teacher, educational administration, and government or governance to be the perspectives used in research articles on AIEd. The SLRs also synthesize that learning, teaching, and/or administrative tasks that AI commonly support are personal & professional learning, resource generation, adaptive content delivery, learner autonomy, learning outcomes monitoring, resource allocation, course scheduling, and data-driven decision making.

2.2 Innovation Resistance

Innovation and technology adoption are usually viewed with the positive lens where factors enabling users to accept and show affirmative intention to use a digital system or application. Some of the theories used in AI technology adoption studies in the past five years include the Unified Theory of Acceptance and Use of Technology, Theory of Planned Behavior, Technology Acceptance Model, and Diffusion of Innovation. Nonetheless, researchers should also shed light on negative aspects of technology adoption, given resistance to innovation as a normal behavior by certain users especially when the innovation brings disruptions to routines and norms.

The innovation resistance theory (IRT) was developed by Ram and Sheth (1989) to explain why consumers resist product innovations and how to adjust marketing strategies to address the functional and technological barriers. Usage, value, and risk barriers are functional barriers that arise due to perceived changes resulting from the use of innovations. Psychological barriers make up the second group, including tradition and image barriers, as conflict with existing beliefs arise from innovation adoption.

The IRT has been used to study resistance to general innovations and technology-enabled ones. However, the application of the IRT on AI in education remain to be underdeveloped. Past research on IRT in education mostly take the students' perspective, such as on the use of e-portfolios (Chae & Lee, 2021), massive open online courses (MOOCs) (Dang, et al, 2022 & Ray, et al, 2022), and LMS (Kim & Park, 2023). On the other hand, AI technology adoption studies using the IRT are within the context of other industries, including e-commerce, health care, customer relations, manufacturing, and personal computing.

2.3 Other Barriers to Innovation

Technological characteristics of innovation (Panda et al, 2024 & Tafazoli, 2024) and the user's digital self-efficacy (Ulfert-Blank & Schmidt, 2022) are found to be other determinants of intention to use AI tools and applications. These are different from the barriers indicated in the IRT as the former is about other technological issues, while the latter is about perceived user capabilities that come with the human-machine interactions brought about by 5IR technologies (Zizic et al, 2022). Therefore, we propose an extended version of the IRT to include technological barriers and self-inefficacy/perceived incompetence as determinants of resistance to innovation in this study.

2.4 Instructional Design

AI technology adoption in education can be studied based on the different teaching and/or learning activities they are implemented in. Instructional design is an iterative process that ensures the effective acquisition of skills and knowledge through the creation and delivery of various learning strategies (Merrill et al, 1996). Resistance may vary depending on which phase or activity in the instructional design process AI will be used in. While some previous studies on AI technology adoption in education include teacher perspectives, they do not explicitly map out the use of AI according to the instructional design process or instructional activities performed by an educator. Innovation resistance can be studied using the ADDIE Model, which is comprised of five phases that make up the acronym: Analysis, Design, Development, Implementation, and Evaluation. It is used by educators to systematically conduct learning needs assessment, identify learning outcomes, develop learning plans and materials, deliver instruction, and evaluate the results of such instructional activities (Molenda et al, 1996).

Alternatively, expected teaching skills can be used to see where AI tools are being utilized aside from the methods and strategies performed as part of instructional design. The SFIA Foundation developed a set of global standards that describe the competencies and skills of various contemporary professions in the digital world, including those of teaching practitioners (SFIA Foundation, 2024). These competencies and skills are defined across various levels of responsibility and can be used in further classifying the activities performed as part of the instructional design process.

3. Research Design

3.1 Research Questions

There is a gap in the existing literature on AI in education, specifically on the resistance to AI-enabled instructional design. Consequently, this research aims to address the gap by answering the research question: *"How does innovation resistance affect the integration of AI tools for instructional design in higher education?"*

Moreover, this research will be answering the following specific questions:

- How are AI tools and applications currently used for instructional design in higher education?
- How does AI integration vary per skill level of higher education teaching practitioners?
- What are the functional and psychological barriers that contribute to resistance in the use of AI for instructional design activities?
- How do technological barriers and self-inefficacy affect resistance to AI integration in instructional design & delivery?

3.2 Methodology

This research will adopt a mixed-method approach in answering the aforementioned research questions. Aside from the quantitative method through surveys being common in technology adoption studies, the addition of qualitative data will provide more insights into the barriers and why they were identified by respondents as such.

3.2.1 Data Collection

Survey questionnaires based on past studies (e.g. Kaur et al, 2020) will be used to gather quantitative data on the current use of AI, as well as the functional, psychological, technological, and self-inefficacy barriers in teaching and learning development. Structured interviews will be conducted to collect additional information about the barriers identified by the respondents.

The items in the questionnaire and structured interviews will also be structured using the SFIA 8 skills catalog for Teaching Practitioners, including Teaching, Subject Formation, Learning Delivery, Learning Design and Development, and Methods & Tools (SFIA Foundation, 2024). It is to be noted that should the SFIA 9 version of the illustrative skills profiles be made available, it will be used in place of the current version.

Purposive sampling will be used to determine 50 participants for the survey, who will be higher education faculty from colleges and universities in Metro Manila. Participants should have general knowledge about available AI tools that can be used for instructional design and delivery, but do not necessarily need to have prior experience in using them. From those who answered the survey, participants will be selected via convenience sampling to undergo the structured interview.

3.2.2 Analysis

The quantitative data will be analyzed using partial least squares structural equation modeling (PLS-SEM) to assess the formulated hypotheses. On the other hand, the qualitative data will be processed using thematic analysis to categorize the barriers into functional, psychological, self-efficacy, and technological barriers. The thematic analysis may also result to other barrier categories aside from the ones currently identified.

4. Research Contribution

This research will provide significant insights to the study of technology adoption and innovation resistance on the use of AI in higher education by exploring barriers specific to the integration of AI tools and applications in instructional design activities. As majority of technology adoption studies use quantitative methods, the inclusion of qualitative data will yield richer information about the covered phenomenon. Moreover, the results may aid in the formulation of programs to increase educators' proficiency and knowledge in AI technology use for them to harness its capabilities for academic productivity and efficiency. Furthermore, the research output may enable policy development in educational institutions and government agencies to address the concerns on the responsible and ethical use of AI for teaching and learning development.

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