INFORMATION SYSTEMS EDUCATION JOURNAL

Volume 23, No. 6
November 2025
ISSN: 1545-679X

In this issue:

iscap
Information Systems & Computing Academic Professionals

The **Information Systems Education Journal** (ISEDJ) is a double-blind peer-reviewed academic journal published by **ISCAP** (Information Systems and Computing Academic Professionals). Publishing frequency is five times per year. The first year of publication was 2003.

ISEDJ is published online (https://isedj.org). Our sister publication, the Proceedings of the ISCAP Conference (https://iscap.us/proceedings) features all papers, abstracts, panels, workshops, and presentations from the conference.

The journal acceptance review process involves a minimum of three double-blind peer reviews, where both the reviewer is not aware of the identities of the authors and the authors are not aware of the identities of the reviewers. The initial reviews happen before the ISCAP conference. All papers, whether award-winners or not, are invited to resubmit for journal consideration after applying feedback from the Conference presentation. Award winning papers are assured of a publication slot; however, all re-submitted papers including award winners are subjected to a second round of three blind peer reviews to improve quality and make final accept/reject decisions. Those papers that are deemed of sufficient quality are accepted for publication in the ISEDJ journal. Currently the target acceptance rate for the journal is under 35%.

Information Systems Education Journal is pleased to be listed in the Cabell's Directory of Publishing Opportunities in Educational Technology and Library Science, in both the electronic and printed editions. Questions should be addressed to the editor at editor@isedj.org or the publisher at publisher@isedj.org. Special thanks to volunteer members of ISCAP who perform the editorial and review processes for ISEDJ.

INFORMATION SYSTEMS EDUCATION JOURNAL

Editors

Beyond Technical Skills: Uncovering Durable Competencies Through Multi-Level Stakeholder Analysis

Ae-Sook Kim*
ae-sook.kim@quinnipiac.edu

Kiku Jones
kiku.jones@qu.edu

Guido Lang
Guido.lang@quinnipiac.edu

Holly J. Raider
holly.raider@quinnipiac.edu

Aamer Sheikh
aamer.sheikh@quinnipiac.edu

Kathleen Simione
kathleen.simione@quinnipiac.edu

Quinnipiac University
Hamden, CT 06518 USA

Abstract

The persistent skills gap in the workforce, exacerbated by rapid technological advancements, has become a critical global issue across sectors. In collaboration with the International Professional Services Organization (IPSO), this study conducted 75-minute focus group interviews in May 2024 with three distinct groups: recent college graduates, master's and doctoral-level graduates, and managers with five or more years of professional experience. Each group, consisting of four participants, was recruited by the IPSO, and they have diverse backgrounds in education, gender, ethnicity, and region. Each interview was audio-recorded and transcribed. Manual content analysis across groups identified metacognitive skills such as reading the room, learning how to learn, self-directed learning, and navigating ambiguous situations as key durable skills defined as transferable competencies across roles, companies, industries, and over time. Focus groups also highlighted critical thinking, communication, and professionalism; however, technological skills were notably absent from the responses. Addressing the findings requires collaborative efforts. Higher education institutions (HEIs) should systematically embed those durable skills across curricula from the first year through graduation. Industry partnerships are highly recommended as they facilitate unstructured real-world learning opportunities. Most critically, students must take active ownership of their learning journey.

Keywords: skills gap, career readiness, durable skills, metacognitive skills, technical skills, focus group

Recommended Citation: Kim, A.-S., Jones, K., Lang, G., Raider, H., Sheikh, A., Simione, K. (2025). Beyond Technical Skills: Uncovering Durable Competencies Through Multi-Level Stakeholder Analysis. *Information Systems Education Journal,* v23, n6, pp 4-18. DOI#: https://doi.org/10.62273/IKXH4521.

* Correspondence should be addressed to Ae-Sook Kim at ae-sook.kim@quinnipiac.edu. All authors except the first are listed alphabetically.

Beyond Technical Skills: Uncovering Durable Competencies Through Multi-Level Stakeholder Analysis

Ae-Sook Kim, Kiku Jones, Guido Lang, Holly J. Raider, Aamer Sheikh and Kathleen Simione

1. INTRODUCTION

Today's economy is driven by rapid technological advancement. Even though artificial intelligence (AI) and advanced automation give us productive gains across sectors, it also adds significant challenges by shifting our demands for skills (Wingard & Farrugia, 2021). In fact, jobs requiring social and emotional skills have experienced the greatest wage growth in recent decades, a shift driven by automation reducing the need for routine tasks (Deming, 2017). Looking ahead, the World Economic Forum (2025) reports that 59% of the world's workforce needs training by 2030 to upskill or reskill to adapt to the rapidly evolving skills demands. Similarly, Deloitte (2020) and McKinsey Global Institute (2024) both project that demand for basic cognitive skills will decrease due to AI integration, while demand for advanced technological skills and social-emotional capabilities continues to rise.

Social and emotional skills and higher cognitive skills are considered durable skills critical for career success due to their long-lasting impact and transferability across jobs, roles, and sectors. However, nearly one-third of organizations struggle to fill positions requiring these competencies (Deloitte Insights, 2020). This skills gap significantly concerns both employers and higher education institutions (HEIs) as unfilled positions incur a substantial economic impact alongside employee training and retraining costs (Levesque, 2019). The gap directly affects economic productivity, growth, and competitiveness (Kenan Institute of Private Enterprise, n.d). HEIs bear the critical responsibility of preparing students successfully for their careers.

To address the skills gap issues, this study, in collaboration with an International Professional Services Organization (IPSO), conducted three focus group interviews with employees of this IPSO. Interviewees included recent college graduates, recent master's and doctoral-level graduates, as well as managers. We expect these three different focus groups to provide insight into identifying the skills gap among recent graduates. To address identified deficiencies, this study further proposes potential solutions for HEIs.

2. LITERATURE REVIEW

Durable Skills and Skills Gap

The Business Higher Education Forum (BHEF) & Burning Glass's comprehensive study in 2018 analyzed about 56 million resumes and over 150 million job postings and concluded there was a clear skills gap. Even though job candidates need blended skills in three groups of foundational skills, that are human skills, business enablers, and digital building blocks, less than 20% of the job seekers listed skills in their resumes in all three groups. In the new era of the digital economy, in-demand skills are constantly updating. The skills gap is not only a problem for high-level talent but also for the middle-level skills credentials which include postsecondary sub-baccalaureate certificates and associate's degrees. The Georgetown Center on Education and the Workforce (2024) found that over 25% of middle-level skills credentials do not have a direct occupational match (Strohl et al., 2024).

Which skills are in high demand now, and which will be in the future? In technology-driven economies, the traditional soft/hard skills distinction fails to capture dynamic changes in the demand for skills. Daniel (2020) underscores a need for a new skill-development framework in consideration of the following three critical questions: "Are skills more durable or perishable? Are skills transferable across roles, job families, or industries? Are skills in demand, and will they be so in the future?" (para. 4) Capturing the essence of these questions, the term 'durable skills' is preferred over 'soft skills' because those skills have a long-lasting impact. Durable skills are indispensable, critical to career success, and in high demand. For instance, Mursion's study (2021, as cited in Pelosse, 2022) reported 44% of HR professionals prefer applicants possessing strong durable skills over those holding strong technical skills. However, durable skills are often found to be lacking in graduates. Even though 70% of the requested skills on job postings are durable skills, on average about 70% of employers across sectors report trouble finding the skilled talent needed (Cole et al., 2021; ManpowerGroup, 2024). This shortage has increased by 32% as compared to 2015 (Pelosse, 2022).

American Succeeds defines durable skills as "a combination of how you use what you know - skills like critical thinking, communication, collaboration, and creativity - as well as character skills like fortitude, growth mindset, and leadership" (Cole et al., 2021, p.9). In related studies, various terms have been used to describe durable skills which include but are not limited to 'essential (soft) skills,' 'employability skills,' '21st century skills,' 'human skills.' After analyzing 82 million job postings, American Succeeds identifies communication, leadership, metacognition, critical thinking, and collaboration as the top durable skill competencies, listed by their ranking, that are in high demand (Cole et al., 2021; Hutson et al., 2023).

As durable skills are interpersonal, intrapersonal, or behavioral in nature, they are difficult to measure and credential. They are also given less priority in teaching at HEIs due to an overemphasis on knowledge-based learning and hard skills (Mahmud & Wong, 2022). Traditional teaching methods like lecture-based teaching have little to do with fostering durable skills. Instead, non-traditional methods such as gamification, simulation, role-playing, inquiry-based, service, project-based, and experiential learning better assist in nurturing durable skills (Almeida & Morais, 2023; Mahmud & Wong, 2022; Tan et al., 2022). To bridge the skills gap, the first step is to enhance the awareness of faculty at HEIs on the importance of critical durable skills for students and to engage faculty in incorporating those skills into the existing course structure (Almeida & Morais, 2023; BHEF & Burning Glass, 2016). Pedagogical innovations are essential, not optional. Furthermore, to align education with industry market needs, HEIs are strongly encouraged to collaborate with business leaders to develop work-based learning programs (BHEF & Burning Glass, 2016; Fox, 2024).

Discipline Specific Literature on Skills Gap

There have also been extensive studies on the skills gap within various specific business disciplines. In prior studies, researchers have primarily employed surveys to determine the nature and extent of the skills gap. It appears that most of the skills gap can be attributed to the lack of durable skills among recent graduates as opposed to hard or technical skills. Even when employers provide opportunities for recent graduates to obtain durable skills, there appears to be a different perception of such opportunities among recent graduates. A survey of Human Resource (HR) managers in German and Italian companies as well as students and recent graduates of a European business school employed in Germany and Italy found that approximately 80 percent "of HR managers indicate they offer formal training to young graduates and that they are involved in the performance appraisal sessions, while only 22 percent of students confirm they receive formal training and only 26 percent declare to be inserted in a performance appraisal process" (Succi & Wieandt, 2019, p. 114). These results show the need for employers to communicate more clearly with their employees and involve new and recent employees in opportunities to learn durable skills. The AACSB also recognizes the skills gap and recently held a roundtable discussion in Barcelona between academic leaders and business leaders to brainstorm about how business and academia can cooperate with each other to bridge the skills gap. Specifically, the AACSB recommends that universities help students learn durable skills by teaching presentation skills, building resilience among students, teaching students how to frame problems, help students develop maturity through experiential learning, providing mentorship, and teaching and modelling values for students (AACSB, 2024).

Stanton and Stanton (2020), Mitchell et al. (2021) and Umamaheswaran et al. (2023) examine the skills gap among recent graduates of business analytics and information systems programs. Stanton and Stanton (2020) document that employers want recent graduates in these disciplines to possess the following essential skills: analytical, communication, problem solving, teamwork and being innovative. They remind educators to use assignments and projects that enable students to learn these skills. Mitchell et al. (2021) also note the importance of such skills and recommend educators use team-based projects that ideally involve students from multiple disciplines, and multiple assignments to help students develop such skills. Umamaheswaran et al. (2023) report on the importance of durable skills in business analytics jobs and suggest the use of experiential learning to help enable students to learn such skills. Finally, Han and Ren (2024) confirm, studying job ads in China, that big data professionals need to possess communication, leadership and teamwork skills and propose that universities work with alumni and industry partners to enable students to obtain such skills through real-world practical experiences.

Several recent papers have documented the skills gap between what accounting students learn in universities and what accounting firms expect from these students in a professional setting and that this gap exists not just in the United States but also in other countries (Burns et al., 2022; McCrary, 2022, Dolce et al., 2020). Berry and Routon (2020) use a large sample of accounting majors to examine whether accounting majors improved their skills in their undergraduate degree programs, and they report the greatest improvement in their hard or technical skills. However, there is less improvement in durable skills. The accounting profession has included communication, decision-making, and leadership, as necessary professional core competencies for accountants (AICPA, 2018). Thus, educators need to consider how best to help equip accounting students with these essential skills. Burns et al. (2022) recommend that accounting programs use problem-based, team-based, and peer-assisted learning as well as reflection to help enable accounting students to learn durable skills.

Almeida and Devedzic (2022) document the importance of durable skills in entrepreneurship. The authors use 38 essential skills specified in the European Entrepreneurship Skills Framework developed by the European Commission and find skills such as emotional intelligence, persistence, and resilience are particularly important for Portuguese and Serbian entrepreneurs. Ferreira et al. (2023) document that there seems to be an increased emphasis on the importance of these skills after the COVID-19 pandemic in advertising and digital marketing. Specifically, "the prevalence of soft skills training had increased in 2020. In 2019, soft skills training tended to be focused on the company culture and workplace environment, with respondents suggesting that training was required in basic communication etiquette, teamwork, client communication, negotiation skills, and public speaking. In 2020, soft skills seemingly focused less on company culture and more on communication both within and outside of the organization. Several respondents indicated that new employees would receive training in basic interpersonal skills and learning how to communicate between departments" (Ferreira et al., 2023, p. 42-43). In addition, adaptability was the skill identified by survey respondents as the most important for new employees' success in advertising and digital marketing careers.

Guidotti et al., (2023) document that soft skills are especially important in sports management. The authors emphasize the importance of lifelong learning and call upon HEIs to consider utilizing interactive learning and teaching techniques along with internships to help sports management students learn crucial soft skills. Such skills are also of great importance in the supply chain industry. Bak et al. (2019) and Fantozzi et al. (2024) document the key role that soft skills such as communication play in supply chain management positions and call on educators to modify their teaching methods and work with employers to create opportunities for students to learn these essential skills.
All in all, the skills gap has been well documented in various business disciplines. HEIs appear to be better at imparting technical skills to their students. However, employers report that their new employees lack durable skills like communication, decision-making, leadership, problem solving, teamwork, and being innovative.

3. CAREER READINESS FRAMEWORK

The National Association of Colleges and Employers (NACE, 2022) defines career readiness as "a foundation from which to demonstrate requisite core competencies that broadly prepare the college educated for success in the workplace and lifelong career management" (NACE, 2022, p. 9).

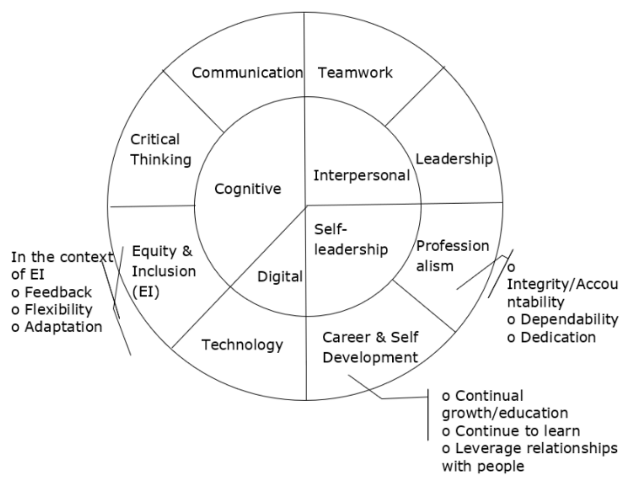


Figure 1. Career Readiness Framework

The NACE lists critical thinking, communication, equity & inclusion, teamwork, leadership, professionalism, career & self-development, and technology as the core competencies. We adopt these eight competencies as the career readiness framework for this study. Seven of the competencies fall into broader durable skills categories which are cognitive, interpersonal, and intrapersonal skills. The career readiness framework is presented in Figure 1.

4. METHODOLOGY

This research is part of an ongoing collaboration between the authors' university – specifically the School of Business and an IPSO. The questions for the focus groups (see Appendix A) were developed collaboratively with representatives from the IPSO. Three focus groups were conducted on-site at the IPSO at the end of May 2024. Each focus group lasted 75 minutes, consisted of four participants from the IPSO, and was facilitated by two of the authors. Four participants are the minimum size recommended for focus groups (Krueger & Casey, 2014). The composition of the three multi-level focus groups reflected different career stages within the organization. The recent college graduate group comprised analysts and consultants with business or STEM-designated majors. The recent graduate program alumni group included participants with full-time and part-time MBA degrees, MS in Business Analytics, and a PhD. Their positions at IPSO included analyst and consultant roles. The participants in these two focus groups had up to two years of post-graduation professional experience. The manager focus group consisted of managers and senior managers at the IPSO with supervisory responsibility for groups with characteristics similar to the other two focus groups, but not necessarily supervisors of the specific individuals in the other focus groups. Participants in this focus group had between five and 20 years of professional experience.

For all three focus groups, the IPSO strived to have broad representation, including participants from public and private sector business units with varied industry and subject matter expertise. The IPSO also ensured the focus groups were diverse in educational experience, major area of study, gender, ethnicity, and region. Despite the efforts undertaken to ensure a broad representation in the focus groups, the participants ultimately constitute a convenience sample of IPSO's employees. Each focus group was audio recorded and subsequently transcribed. The average word count of the three transcripts is 15,430 words (SD = 3,225.77).

The transcripts were analyzed using two sequential methods: (1) a manual content analysis using a collaborative qualitative analysis approach (Richards & Hemphill, 2018) followed by (2) an automated topic modeling analysis using Latent Dirichlet Allocation or LDA (Blei et al., 2003). For the manual content analysis, the authors identified themes iteratively within and across each focus group as recommended for qualitative analysis (Strauss & Corbin, 2015). To this end, we alternated between identifying themes independently and agreeing on identified themes in regularly scheduled group meetings, thus applying the constant comparative method of qualitative content analysis in a collaborative fashion (Gibbert et al, 2008).

Following the manual content analysis, we employed topic modeling using LDA to identify additional themes in each focus group automatically (Jelodar et al., 2019). The optimal number of topics for each focus group was determined based on the metric proposed by Cao et al. (2009). After applying LDA, the most important terms for each topic were extracted and compared across the focus groups.

5. RESULTS

The manual content analysis draws several central themes from the focus group interviews. Those themes are centered on durable skills and are presented in Table 1. For the recent college graduates focus group, there was a central theme of "Reading the room"/Being aware of the organization. This included dimensions such as reading body language, interpreting interpersonal dynamics among others, and being aware of how organizational decisions are made. Interviewees mentioned that understanding the context, current state and situation, the vocabulary used, and figuring out how to add value are challenging, especially at their first job.

Recent College Graduates
• "Reading" the room • Being aware of the organization
Master's & Doctorate-Level Graduates
• Managing stress, balancing work/life • Recognizing the need for continuous learning
Managers
• Seeing how their work impacts other parts of the project/organization, seeing the big picture • Feeling overwhelmed, giving up easily

Table 1: Manual content analysis results

They did not feel that their university experience had prepared them well for unstructured situations. The participants said that they learned by observing other employees who had been there longer and listening to how these employees were able to ask the right questions. Looking at Figure 1, this focus group spoke more about cognitive and intrapersonal durable skills - specifically, critical thinking, communication, and career & self-development.

The central themes of the recent master's and doctoral-level graduates focus group were managing stress and balancing work/life and recognizing the need for continuous learning. This group was caught in a generational divide. This divide put them in a position that required leadership and communication to bridge the divide. In addition, the stress of managing work/life balance led to the best employees leaving. The focus group therefore expressed the need to manage this stress. In addition, they discussed the need for continuous learning. This self-awareness that they have more to learn in the field and that it is a continuous cycle points directly to one of the core competencies in the NACE career readiness framework, career & self-development. This focus group spoke about each of the durable skills categories and in fact touched on all seven of the core competencies associated with them. For intrapersonal, the professionalism core competency was included when the participants discussed their desire to ensure that they meet the increasing responsibilities of their role. For cognitive skills, communication was described when discussing the need to bridge the divide between the generations. Critical thinking was included when discussing both the need to find ways to manage stress and balance work and life. Equity and inclusion were also included here when the topic of work/life balance was discussed. Also, when talking about obtaining additional degrees/certifications, discussion of the ability of some to be able to take classes full-time vs. part-time and the differences in the ability to take part in extracurricular activities. For interprofessional skills, this group brought in the discussion of teamwork and leadership. They discussed the importance of learning how to be on a team and how to provide feedback to others.

The manager focus group recognized the challenges in new/recent hires not seeing the "big picture" and/or how their work impacted other parts of the project/organization. This challenge appears to be centered on the issue that new/recent hires are unable to see the connections of their work with those of others in the organization or the larger community. This points back to the core competencies of teamwork, leadership, and critical thinking. The managers also highlighted the challenges of helping to prevent new hires from feeling overwhelmed and "giving up" so easily. Some participants also shared that new/recent hires who encounter challenges choose just not to complete the task rather than conduct research on how to resolve the challenges or ask for help. This issue appears to point to both professionalism and communication.

The central themes of the recent college graduates and the manager focus groups tend to complement each other. The recent college graduates focused on the intrapersonal competency of career and self-development and the cognitive competencies of critical thinking and communication. The manager focus group indicated there was a lack of skills among new/recent hires in the areas of interpersonal competencies (teamwork and leadership), intrapersonal competency (professionalism), and cognitive competencies (critical thinking and communication). Between the two groups they mentioned each of the core competencies but one, equity & inclusion. However, during the manager focus group, the participants did indicate that the new/recent hires often were involved in the Diversity, Equity and Inclusion (DEI) and sustainability initiatives at the IPSO. The recent master's and doctoral-level graduates focus group covered all competencies. This is fitting as they are in that middle ground both generationally and professionally.

The automated topic modeling analysis using LDA identified two topics for each focus group along with the top 10 most important terms associated with each topic. The topics were rather broad in nature, as indicated by such terms as "learn", "question", "skill", "business", "help", "career", "people", etc. More information about the topic modeling analysis results can be found in Appendix C. As a result, no additional themes beyond those found by the manual content analysis were identified.

6. DISCUSSION

What We Have Learned

Our findings point to the need for greater durable skill development among college students before their first jobs and for graduate program alumni as they take on roles of increasing complexity or responsibility.

Our research offers unique insights that go beyond extant research on employer reports of skills gap by using focus group discussions and a grounded theory approach to examine the career readiness of recent college and graduate program graduates.

The interview protocol in the focus groups used open-ended questions about initial work assignments and what knowledge, skills, or abilities were the most helpful in addressing the challenges recent graduates faced at work. Although the interview protocol did not specifically ask about durable skills or technical skills, it is striking that neither the recent college graduates in their first job nor the recent graduate program graduates cited technical knowledge or skills as most helpful. Rather, both groups pointed to durable skills as the most needed and most helpful. In fact, even when technical skills were mentioned, such as a client using a new platform or a different programming language, the focus group participants emphasized the importance of metacognitive skills such as learning how to learn, self-directed learning, adapting their current knowledge to an unfamiliar domain, judgment in knowing when and (from whom) to ask for help. It is poignant that focus group participants did not mention the lack of technical knowledge or technical skills as a challenge.

Also consequential is that members of the recent college graduate group noted their first job was challenging because they had to navigate ambiguous situations and address complex problems that lacked formulaic solutions. They observed that their college experiences did not prepare them for these challenges, as their coursework typically included detailed grading rubrics, problems with knowable solutions (and answer keys), and, in general, offered clear and structured pathways for academic success. They indicated that mentors, those who are either assigned or emerged through organic connections, helped them to navigate those situations.

These findings point to an important opportunity for HEIs to build durable and metacognitive skills through integration across curricula and as students progress to graduation. Conceptually, strengthening critical thinking and problem-solving abilities involves learning objectives and pedagogies that prepare students to apply knowledge in increasingly ambiguous and complex situations so that by graduation they are able to apply knowledge in novel situations, such as competency-based assignments. At the same time, the findings point to a need to intentionally, increasingly hold students accountable for their role in their learning and development. Examples of accountability include meeting deadlines, effective communication, and class participation. Additionally, actively building professional networks assists students in preparing for their future careers.

Potential Solutions

Although numerous previous studies acknowledge the skills gap, identify the skills deemed essential, and point out the need for curricular change, specific recommendations narrowing the skills gap are limited. That said, internships and real-world experiences are frequently suggested to help develop durable skills (Almedia & Morais, 2023; Arvanitis et al., 2022; De Villiers, 2010; Tan et al., 2022). Tan et al. (2022) suggest that internships and other real-world experiences improve students' cognitive skills, including planning and analyzing, critical thinking, and problem-solving. The recent graduates focus groups in our study also stressed the value of internships and other experiential learning in providing them with an opportunity to develop critical thinking, problem solving, communication, and interpersonal skills.

Although internships certainly provide a benefit, students typically do not have the opportunity to participate in an internship until their junior year, resulting in only one internship experience prior to their first full-time job. In addition, an internship opportunity might not be available for all students, and in some cases, students' circumstances might not allow them to take advantage of an external internship. Alternatively, we suggest embedding internships or some form of experiential learning into individual courses early in a student's program with integration across the curriculum. This can take the form of virtual simulations that model internship experiences if actual experiences are not practical to deploy. This could help support and reinforce skill development and better prepare students for their external internships.

Durable skills can also be developed with other hands-on learning including active learning and problem-based learning (Mahmud & Wong, 2022), both of which could facilitate critical thinking skills. All three of our focus groups recognized the importance of incorporating this type of learning. The managers emphasized the need to move away from structured assignments and tasks. They recommended adding complexity and providing learning opportunities that were "messy," providing students with conditions that simulate what they would see in the workplace. Partnering with industry to develop these unstructured more real-world learning opportunities can facilitate students' adaptability, another critical skill noted by employers and the managers focus group. It is important for students to be aware and prepared to adjust for changes in deliverables and due dates and other workplace changes. The partnership can and should extend beyond individual assignments to courses and programs to further provide more real-world experiences. As we discussed with the IPSO in the study, this can be done with the creation of micro-credentials and certifications.

Additionally, both the undergraduate and graduate student focus groups noted that learning to ask questions and recognizing the need for continuous learning were critical. Arvantis et al.'s study (2022) concluded that this "learning to learn" was critical to narrowing the skills gap. This was confirmed in our focus group interviews. Arvantis et al. (2022) also note that universities "should find ways to embed educational practices in social and work interactions" (p. 71) to facilitate flexibility, adaptability, initiative, and autonomy; all considered key soft skills. Regarding social and work interactions, we found it important to provide opportunities for students to learn about career expectations including appropriate work responsibility and timelines, professional etiquette and communication. This is another area where education and industry can partner in the development of mentoring programs and other educational opportunities.

Clearly, focused efforts are needed by educators, industry, and students to narrow the skills gap. As noted, for educators, these efforts can include increasing internship and experiential learning opportunities inside and outside the classroom. They can also include creation of courses, assignments and programs that facilitate skill building and other programmatic changes. Industry can assist by collaborating with educators on curricular development to meet the needs of a dynamic environment and supporting students by providing mentorship and internship opportunities.

7. CONCLUSION

Contributions

This study makes several important theoretical and practical contributions. Theoretically, this study provides additional evidence for the importance of durable skills in academic curricula, which are often overshadowed by technical skills. Moreover, this study brings to light certain durable skills that have been overlooked in the literature, such as one's ability to "read," or be aware of, the organization/room and seeing how one's work impacts other parts of the project/organization.

Additionally, this study highlights significant differences in the perceived importance of skills across career stages, specifically between recent graduates, master's and doctoral-level graduates, and managers. Most previous studies identified skills gaps from the perspectives of employers. A limited number of studies incorporated both employers' and employees' perspectives, and those were based on survey methods. The current focus group interviews with multi-level participants help us to collect a deeper and richer experience of the participants through the social interaction of the group (Gundumogula & Gundumogula, 2020; Kitzinger, 1995). The focus groups of both employees and managers helped us to draw the common themes from each group and enabled us to compare similarities and differences in knowledge and experience from multi-level focus groups. To the best of our knowledge, this is the first study to utilize this approach (Winke, 2017).

Practically, this study provides actionable recommendations for HEIs aiming to better prepare students for the workforce. Specifically, it points to the need for decreasing scaffolding coupled with increasing ambiguity and complexity as students advance in their programs. Furthermore, it suggests integrating durable skills into curricula through non-traditional teaching methods such as experiential learning, role-playing, and simulations. This study also emphasizes the importance of collaboration between educational institutions and industry to help students develop durable skills through internships, mentoring programs, and real-world projects.

Limitations

This study is not without its limitations. First, there are limitations stemming from the use of focus groups from one IPSO. The focus groups were representatives from the IPSO selected by the IPSO. As such, certain biases may have been inadvertently introduced in the participant pool. Additionally, the authors moderating the focus groups may have influenced the participants' individual responses. Second, the number of participants in each focus group was on the low end of the recommended size (Krueger & Casey, 2014). Likewise, there was only one focus group for each participant category. As a result, the focus groups only captured a limited range of viewpoints. Third, the interpretation of the data was subject to the authors' biases and perspectives. While efforts were made to reduce these biases, it is possible that other researchers may have identified different themes resulting from the focus groups. As such, findings from this study should be interpreted with caution.

Future Research
Future research would benefit from increasing the size and diversity of the participant pool outside of the IPSO using independent focus group moderators. This would help capture a broader range of perspectives. Additionally, future research may benefit from using survey-based or longitudinal research designs to triangulate this study's findings. Likewise, future research should include employer perspectives from different industries and policy makers. Lastly, future research could be conducted in different geographic regions and cultures.

8. DISCLAIMER

The views, opinions, findings, and conclusions expressed in this paper are strictly those of the authors and do not necessarily reflect the view of Deloitte. Deloitte takes no responsibility for any errors or omissions in, or for the correctness of, the information contained in this paper.

9. ACKNOWLEDGEMENTS

The present manuscript was made possible through a valuable partnership with Deloitte Consulting, LLP. We would like to express our special appreciation to Ashton Braddock, Blythe Kladney, Roy Mathew, Sunjae Park, Divya Periakarappan, and Sophia Sodhi from Deloitte. Their insights and collaboration enriched the quality of the work and have been vital throughout the process.

10. REFERENCES

AACSB. (2024, March 20). What Can Business Schools and Industry Do Together? Retrieved July 10, 2024, from https://www.aacsb.edu/insights/articles/2024/03/what-can-business-schools-and-industry-do-together

AICPA. (2018). AICPA Pre-Certification Core Competency Framework. Retrieved July 10, 2024, from

https://us.aicpa.org/interestareas/accountingeducation/resources/corecompetency

Almeida, F., & Devedzic, V. (2022). The Relevance of Soft Skills for Entrepreneurs. *Journal of East European Management Studies*, 27(1), 157 – 172. https://doi.org/10.5771/0949-6181-2022-1-157.

Almeida, F., & Morais, J. (2023). Strategies for Developing Soft Skills Among Higher Engineering Courses. *Journal of Education,* 203(1), 103–112. https://doi.org/10.1177/00220574211016417

Arvanitis, A., Touloumakos, A. K., Dimitropouloul, P., Vlemincx, E., Theodorou, M., & Panayiotou, G. (2022). Learning How to Learn in a Real-Life Context: Insights from Expert Focus Groups on Narrowing the Soft-Skills Gap. *European Journal of Psychology*, 81(3), 71–77. https://doi.org/10.1024/2673-8627/a000027

Bak, O., Jordan, C., & Midgley, J. (2019). The adoption of soft skills in supply chain and understanding their current role in supply chain management skills agenda: A UK perspective. *Benchmarking: An International Journal*, 26(3), 1063-1079. https://doi.org/10.1108/BIJ-05-2018-0118

Berry, R., & Routon, W. (2020). Soft skill change perceptions of accounting majors: Current practitioner views versus their own reality. J*ournal of Accounting Education*, 53, 1-12. https://doi.org/10.1016/j.jaccedu.2020.100691

Blei, D. M., Ng., A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, 3, 993-1022. https://dl.acm.org/doi/10.5555/944919.944937

Burns, C. S., Fischer, M. L., Latham, C. K., Matuszewski, L. J. & Sage, J. A. (2022). Leveraging medical education resources to enhance instruction in accounting education. *Journal of Accounting Education*, 60, 1-19. https://doi.org/10.1016/j.jaccedu.2022.100785

Business Higher Education Forum (BHEF) & Burning Glass. (2018). The New Foundational Skills of the Digital Economy. Retrieved July 10, 2024, from https://www.bhef.com/sites/default/files/BHEF_2018_New_Foundational_Skills.pdf

Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing (72)*, 7–9: 1775–1781.

https://doi.org/10.1016/j.neucom.2008.06.011

Cole, L, Short, S., Cowart, C., & Muller, S. (2021, October). The High Demand for Durable Skills. America Succeeds & Ems Burning Glass. Retrieved July 10, 2024, from https://americasucceeds.org/wp-content/uploads/2021/04/AmericaSucceeds-DurableSkills-NationalFactSheet-2021.pdf

Daniel, M. J. (2020, November). Skills aren't soft or hard - they're durable or perishable. *Training and Development Excellence Essentials*. Retrieved July 10, 2024, from https://www.chieflearningofficer.com/2020/10/29/skills-arent-soft-or-hard-theyre-durable-or-perishable/

De Villiers, R. (2010). The incorporation of soft skills into accounting curricula: Preparing accounting graduates for their unpredictable future. *Meditari Accountancy Research*, 18(2), 1-22. https://doi.org/10.1108/10222529201000007

Deming, D. J. (2017). The Growing Importance of Social Skills in the Labor Market. *The Quarterly Journal of Economics, 132*(4), 1593–1640. https://doi.org/10.1093/qje/qjx022

Deloitte Insights (2018). *2018 Deloitte skills gap and future of work in manufacturing study*. Deloitte Development LLC. Retrieved July 10, 2024, from https://www2.deloitte.com/content/dam/insights/us/articles/4736_2018-Deloitte-skills-gap-FoW-manufacturing/DI_2018-Deloitte-MFI-skills-gap-FoW-study.pdf

Deloitte Insights (2020). *Closing the employability skills gap: The answer is simpler than you may think.* Retrieved February 28, 2025, from https://www2.deloitte.com/us/en/insights/focus/technology-and-the-future-of-work/closing-the-employability-skills-gap.html

Dolce, V., Emanual, F., Cisi, M., & Ghislieri, C. (2020). The soft skills of accounting graduates: Perceptions versus expectations, *Accounting Education*, 29(1), 57-76. https://doi.org/10.1080/09639284.2019.1697937

Fantozzi, I. C., Di Luozzo, S., & Schiraldi, M. M. (2024). On tasks and soft skills in operations and supply chain management: analysis and evidence from the O*NET database. *The TQM Journal*, 36(9), 53-74. https://doi.org/10.1108/TQM-04-2023-0104

Ferreira, C., Robertson, J., & Pitt, L. (2023). Business (un)usual: Critical skills for the next normal. *Thunderbird International Business Review*, 65, 39–47. http://doi.org/10.1002/tie.22276

Fox. (2024, May). Blending Working and Learning: What Works to Close the Skills Gap. The Business-Higher Education Forum. Retrieved July 10, 2024, from https://www.bhef.com/article/2024/blending-working-and-learning-what-works-to-close-the-skills-gap

Gibbert, M., Ruigrok, W., & Wicki, B. (2008). What passes as a rigerous case study? Strategic Management Journal, 29, 1465–1474. https://doi.org/10.1002/smj.722

Guidotti, F., Demarie, S., Ciaccioni, S., & Capranica, L. (2023). Sports Management Knowledge, Competencies, and Skills: Focus Groups and Women Sports Managers' Perceptions. *Sustainability*, 15 (10335), 1-25. https://doi.org/10.3390/su151310335

Gundumogula, M. & Gundumogula. M. (2020). Importance of Focus Groups in Qualitative Research. *International Journal of Humanities and Social Science (IJHSS)*, 8 (11), 299-302. https://doi.org/10.24940/theijhss/2020/v8/i11/HS2011-082.

Han, F., & Ren, J. (2024). Analyzing Big Data Professionals: Cultivating Holistic Skills Through University Education and Market Demands, *IEEE Access*, 12, 23568-23577. Retrieved July 10, 2024, from https://doaj.org/article/d621e2844f614837b3a32946a9968106

Hutson, J., Valenzuela, M., Hosto-Marti, B., & Wright, S. (2023). The Role of Higher Education in Developing Durable Skills: Reframing General Education. *Journal of Organizational Psychology, 23*(1), 1-12. https://doi.org/10.33423/jop.v23i1.5851

Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., & Zhao, L. (2019). Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimedia Tools and Applications*, 78, 15169-15211. Retrieved July 10, 2024, from https://dl.acm.org/doi/10.1007/s11042-018-6894-4

Kenan Institute of Private Enterprise. (n.d.). Grand challenge 2025: The skills gap. Retrieved February 28, 2025, from https://kenaninstitute.unc.edu/kenan-insight/grand-challenge-2025-the-skills-gap/

Kitzinger, J. (1995). Qualitative Research: Introducing focus groups. *British Medical Journal*, 311, 299-302. https://doi-org.libraryproxy.quinnipiac.edu/10.1136/bmj.311.7000.299

Krueger, R. A., & Casey, M. A. (2014). *Focus Groups: A Practical Guide for Applied Research*. Thousand Oaks, CA: Sage Publications.

Levesque, E. M. (2019, December 6). Understanding the skills gap—and what employers can do about it. Brookings. Retrieved July 10, 2024, from https://www.brookings.edu/articles/understanding-the-skills-gap-and-what-employers-can-do-about-it/

Mahmud, M. M., & Wong, S. F. (2022). Stakeholder's Perspectives of the Twenty-First Century Skills. *Frontier Education,* 7, 1-8. https://doi.org/10.3389/feduc.2022.931488

ManpowerGroup. (2024). ManpowerGroup Employment Outlook Survey: U.S. Findings. Retrieved July 10, 2024, from https://go.manpowergroup.com/hubfs/GLOBAL_EN_MEOS_Report_3Q24.pdf

McCrary, S. C., (2022). Accounting curricula: Soft skills at the expense of technical competency or a happy merger of the two? *Journal of Education for Business*, 97(3), 204-212. https://doi.org/10.1080/08832323.2021.1910115

McKinsey Global Institute. (May 2024). A New Future of Work: The Race to Deploy AI and Raise Skills in Europe and Beyond. McKinsey & Company. Retrieved February 28, 2025, from https://www.mckinsey.com/mgi/our-research/a-new-future-of-work-the-race-to-deploy-ai-and-raise-skills-in-europe-and-beyond

Mitchell, R. B., Woolridge, R. W., & Johnson, V. (2021). The role of nontechnical skills in providing value in analytics-based decision culture, *Journal of Education for Business*, 96(1), 1-9. http://doi.org/10.1080/08832323.2020.1719961

National Association of Colleges and Employers (NACE). 2022. Development and Validation of the NACE Career Readiness Competencies. Retrieved July 10, 2024, from https://www.naceweb.org/uploadedFiles/files/2022/resources/2022-nace-career-readiness-development-and-validation.pdf

Pelosse, G. (2022, March 11). What are durable skills and why is there a shortage? Forbes. Retrieved July 10, 2024, from https://www.forbes.com/sites/forbeshumanresourcescouncil/2022/03/11/what-are-durable-skills-and-why-is-there-a-shortage/

Richards, K. A. R., & Hemphill, M. A. (2018). A practical guide to collaborative qualitative data analysis. *Journal of Teaching in Physical Education*, 37(2), 225–231. https://doi.org/10.1123/jtpe.2017-0084

Stanton, W. W., & Stanton, A. D. (2020). Helping Business Students Acquire the Skills Needed for a Career in Analytics: A Comprehensive Industry Assessment of Entry-Level Requirements. *Decision Sciences Journal of Innovative Education*, 18(1), 138-165. https://doi.org/10.1111/dsji.12199

Strauss, A., & Corbin, J. (2015). Basics of qualitative research: Techniques and procedures for developing grounded theory (4th ed.). New York, NY: Sage.

Strohl, J., Mabel, Z., & Campbell, K. P. (2024). The Great Misalignment: Addressing the Mismatch between the Supply of Certificates and Associate's Degrees and the Future Demand for Wokers in 565 US Labor Markets. The Georgetown Center on Education and the Workforce. Retrieved July 10, 2024, from https://cew.georgetown.edu/wp-content/uploads/cew-the_great_misalignment-fr.pdf

Succi, C., & Wieandt, M. (2019). Walk the talk: soft skills' assessment of graduates. *European Journal of Management and Business Economics*, 28(2), 114-125. https://doi.org/10.1108/EJMBE-01-2019-0011

Tan, L. M., Laswad, F., & Chua, F. (2022). Bridging the employability skills gap: going beyond classroom walls. *Pacific Accounting Review*, *34*(2), 225–248. https://doi.org/10.1108/PAR-04-2021-0050

Umamaheswaran, S., Fernandes, S., Venkatesh, V. G., Avula, N, & Shi, Y. (2023). What Do Employers Look for in "Business Analytics" Roles? – A Skill Mining Analysis. *Information Systems Frontiers: A Journal of Research and Innovation*, 1-17. https://doi.org/10.1007/s10796-023-10437-y

Wingard, J., & Farrugia, C. A. (Ed.), (2021). *The great skills gap: optimizing talent for the future of work* (1 ed.). Stanford Business Books, an imprint of Stanford University Press.

Winke, P. (2017). Using focus groups to investigate study abroad theories and practice. *System*, 71, 73-83. https://doi.org/10.1016/j.system.2017.09.018

World Economic Forum. (January 2025). Future of Jobs Report 2025. Retrieved February 21, 2025, from https://reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf

APPENDIX A: FOCUS GROUP QUESTIONS

Recent College Graduates / Master's and Doctoral-level Graduates

On-the-job readiness:

1. [For graduates: What specific knowledge, skills, or abilities were you looking to develop by attending graduate school?]
2. Consider a specific project in the first few months/year that you worked on as a full-time employee after you completed your degree:
    a. What were the biggest challenges you experienced?
    b. What knowledge, skills, or abilities were the most helpful to address those challenges?
        i. Which of those knowledge, skills, or abilities were developed in college/university?
        ii. Which experiences, courses, programs, resources, or tools at college/university assist in developing those?
    c. What knowledge, skills, or abilities were needed most but lacking?
        i. Which ones could have been developed during your college/university years?
        ii. Which ones were missing from college/university education?
        iii. Was there any that you thought would be useful but turned out not to be?
    d. To close the gap, what actions did you take? (e.g., any training, consultations, etc.) Could you please share your experience?

Overall holistic:

1. Knowing what you know now, would you choose the same program/major again? If not, what program/major would you pick?
2. What advice would you give to current or future students to be better prepared for the rapidly evolving job market?

Management

Assessment of Staff:

1. Consider a specific team project where recent hires (either undergraduate or graduates) got involved and you managed in the last 2-3 years:
    a. What are the greatest gaps in knowledge, skills, and abilities of the recent hires you have observed?
    b. What do you have to do to close the gaps (e.g., via on-the-job or formal training)?
    c. What could be estimates of the cost of training/retraining the recent hires to close those gaps? (e.g., time and money spent)

A general assessment of the recent hires' knowledge, skills, and abilities

1. What specific knowledge, skills, and abilities do you consider as key differentiators in your hiring decisions?
2. Why are those knowledge, skills, and abilities important for your (team) work?
3. How do you assess whether an employee possesses the needed knowledge, skills, and abilities to be effective in their role?

Other:

1. What are the two to three knowledge, skills, and abilities that you would like to prioritize for undergraduates/ graduates to develop during their college/university years?

APPENDIX B: COMMON THEMES FOUND USING MANUAL CONTENT ANALYSIS

Common Themes
Cognitive • Communication • Critical Thinking * • Figure out/deal with ambiguity * • Flexibility (open-minded approach) * • Problem-solving (including creativity) * Interpersonal • Leadership • Collaboration/Teamwork • Giving feedback Intrapersonal • Learning how to learn • Ability to accept & Apply feedback • Learning how to ask questions • Persistence *
Common, Manifest Differently • Adaptability • Mentorship • Relationship Building/Networking

**Themes found in the manager focus group*

APPENDIX C: RESULTS OF AUTOMATED TOPIC MODELING ANALYSIS

Focus Group \ Topics	Topic 1	Topic 2
Recent College Graduates	learn, question, skill, business, talk, time, answer, guess, student, marketing	help, college, people major, class, course, school, mind, experience, career
Recent Master's & Doctoral-level Graduates	skill, learn, people, project, school, graduate, team, help, specific, classroom	time, program, feedback, question, MBA, client, experience, undergraduate, student, class
Managers	talk, feedback, learn, training, person, cost, practitioner, focus, junior, skill	people, hour, team, time, project, client, understand, school, job, week

Conquer the Cloud: Effectively Using the Amazon Web Services Academy Learner Lab for Information Systems Education

Jeff Strain
jeff.strain@byuh.edu
Brigham Young University Hawaii
Laie, HI, 96762, USA

Jim Marquardson
jmarqua@nmu.edu
Northern Michigan University
Marquette, MI 49855, USA

David Lee Gomillion
dgomillion@tamu.edu
Texas A&M University
College Station, TX 77843

Abstract

Information systems students yearn for hands-on, active learning experiences that teach relevant skills. Delivering these experiences requires repeatable, secure, and scalable computing infrastructure. Unfortunately, many institutions struggle with the capital and operational costs of hosting in-house computing environments. Some educational platforms give access to inflexible environments that limit instructors' options for curriculum design. Through the Amazon Web Services Academy, educators can use the Learner Lab environment to provide students with a managed environment for developing code and testing infrastructure in the cloud with modest limitations. We present a set of best practices based on our years of experience teaching Information Systems students in the Learner Lab environment. The best practices address pedagogy, student onboarding, architectural guidance, and curriculum development.

Keywords: cloud computing, computing hardware, AWS Academy Learner Lab

Recommended Citation: Strain, J., Marquardson, J., Gomillion, D., (2025). Conquer the Cloud: Effectively Using the Amazon Web Services Academy Learner Lab for Information Systems Education *Information Systems Education Journal*. v23, n6 pp 19-36. DOI https://doi.org/10.62273/FWMT9408

Conquer the Cloud: Effectively Using the Amazon Web Services Academy Learner Lab for Information Systems Education

Jeff Strain, Jim Marguardson and David Lee Gomillion

1. INTRODUCTION

Cloud computing has revolutionized how organizations manage, maintain, and deploy systems. Organizations demand scalable, secure, and cost-effective solutions; cloud computing can increasingly address these challenges. Educators can leverage these same benefits by embracing the cloud (Merchante et al., 2024; Segec et al., 2021; Qasem, 2019). This paper explores the significance of leveraging cloud computing using the Amazon Web Services (AWS) Academy Learner Lab environment and its impact on Information Systems education.

Why Universities Need the Cloud

Virtual machines provide repeatable, standardized, and segmented computing environments that educators can leverage to teach practical knowledge and skills. Desktop hypervisors (such as Oracle VirtualBox and VMWare Workstation Player) and server hypervisors (such as VMWare ESXi and Proxmox) provide a layer of abstraction so that the same virtual machine should run the same regardless of host computer differences. A critical question universities must ask is, “Where should the virtual machines be deployed?”

Disk, CPU, and RAM limitations on student computers restrict the size and number of virtual machines. Differences in CPU type (e.g., x64, ARM, Apple M) add devices with organizational restrictions increase the configuration challenges. Some student devices, such as phones, tablets, and Chromebooks, cannot support the virtualization of other systems (Brereton, 2022). Whether in-house, by third parties, or in the cloud, hosting lab virtual machines removes the concerns of students needing more compute resources from the virtualization equation.

In-house private clouds require significant capital expenditures and add administrative burden to maintain on-premises computing infrastructure. Additionally, universities must allocate funds for power, maintenance, and upgrades (Murphy & McClelland, 2009). Cloud computing solves many of these university challenges (Mew, 2016). Instead of provisioning infrastructure for peak capacity, universities can elastically provision and deprovision resources as needed. When empowered with the cloud, educators can manage their lab environments without hardware, software, or operational support from their IT departments. The cloud, specifically the Amazon Web Services Academy Learner Lab, makes this possible.

AWS Academy

AWS Academy provides higher education institutions with a hands-on cloud computing curriculum at no cost to institutions or students (Nwokeji et al., 2021). It uses Canvas to organize lesson materials and provide a portal to the real AWS cloud. Students leverage the AWS Academy to prepare for industry-recognized certifications and in-demand jobs. Hundreds of institutions have adopted the AWS Academy for data analytics, Information Systems, cybersecurity, and general cloud awareness (Meyer & Billionniere, 2021).

The AWS Academy is composed of many distinct courses. For example, the Cloud Foundations course teaches principles of cloud computing with readings, videos, and hands-on labs. Except for the Learner Lab environment, all AWS Academy courses contain curriculum, lab exercises, and quizzes developed and supported by Amazon(Moltó et al., 2020). The Learner Lab course is distinct in that it provides more flexibility to the instructor to craft assignments and will remain the focus of the rest of the paper(Correia & Tasker, 2022).

Learner Lab Course

The Learner Lab course provides students with restricted AWS services for ad hoc creation and exploration of AWS services. When an instructor enrolls a student in a Learner Lab course, AWS provides an AWS environment for their personal use. Each student receives a course lab credit amount to spend in the AWS cloud without providing credit card information, and AWS never charges students for resource use. The AWS environment leverages the same AWS resources provided to AWS customers but with some resource usage limitations. Unlike other AWS Academy courses, resources within the Learner Lab persist, allowing students to revisit their work over time. Some resources (such as virtual machines) are automatically powered down after periods of inactivity to help manage credits efficiently. Credits are discussed further in this paper's "Cost Management" section.

The Learner Lab supports inclusivity by removing barriers, like a student who cannot afford a sufficiently powerful laptop to perform labs. The Learner lab lets students experiment with real-world information technology scenarios where they can destroy, create, and extend systems beyond classroom instruction. By working hands-on in cloud environments, students bridge the gap between theory and practice, preparing themselves for the complexities of the professional world.

As educators, we experienced several speedbumps when first teaching within the Learner Lab environment. The purpose of this paper is to share best practices to help educators:

1. Get started with the AWS Academy Learner Lab
2. Prevent accidental abuse of the Learner Lab environment
3. Develop a curriculum to leverage the opportunities in the cloud

By following the principles in this document, educators will reduce time spent developing curriculum, making it easier for students to complete exercises, and ensure compliance with AWS Academy policies.

2. METHODOLOGY

The authors of this paper formed a quorum of experts. Their institutions include a public, research-intensive university, a private, undergraduate-focused university, and a public, regional, comprehensive university. The students at these universities have diverse socioeconomic backgrounds. The authors leveraged the AWS Learner Lab in many courses and collaborated to share their experiences. They identified common strengths and challenges using the AWS Learner Lab. The following sections contain actionable guidance the authors distilled from their experiences, augmented by the pedagogical literature related to teaching with cloud computing.

3. GETTING STARTED WITH THE AWS LEARNER LAB

This section describes how educators can start with AWS Academy and create Learner Lab courses. By necessity, this and subsequent sections refer to many different cloud technologies. A glossary of key terms is included in Appendix A.

AWS Academy Onboarding

Amazon requires that universities become "member institutions" before using the AWS Academy. One university representative becomes the lead responsible for managing the institutional relationship with AWS Academy. This lead must attend online AWS Academy training and accept the AWS terms of service. Once AWS approves the institution, the institution's lead nominates instructors. Instructors complete a short onboarding course before teaching AWS Academy courses. The onboarding process to become a member institution and approve instructors is simple, though it can take several weeks. Figure 1 summarizes this process.

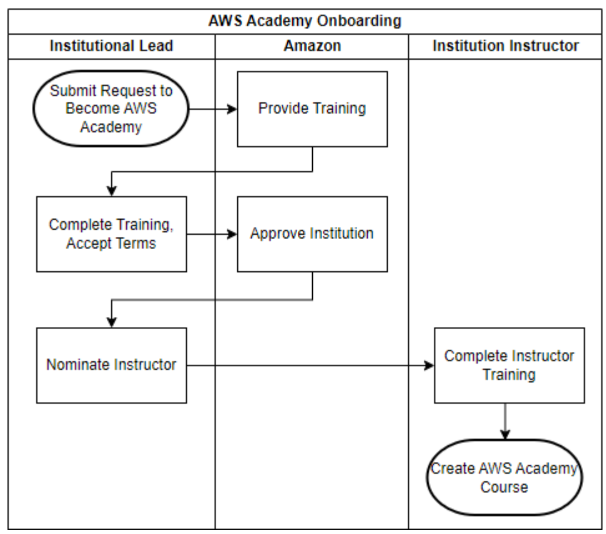


Figure 1 AWS Academy Onboarding Process

AWS Academy LMS

AWS Academy hosts all its courses using the Canvas learning management system (LMS). Instructors can create courses from the AWS Academy catalog. Instructors invite students to courses using email addresses. While most AWS Academy courses include instructions and labs curated by AWS, the Learner Lab provides educators with a sandbox in which educators provide custom instruction and labs.

Classroom Management

We recommend that educators create a Learner Lab section in the AWS Academy LMS for each university course offering. Segmenting courses limits the fallout if one section is decommissioned prematurely due to egregious violations. Educators should be aware that an entire Learner Lab course could be unpublished due to technical problems or severe policy violations. The workflow for creating a course and how the student enrollment process occurs is in Figure 2.

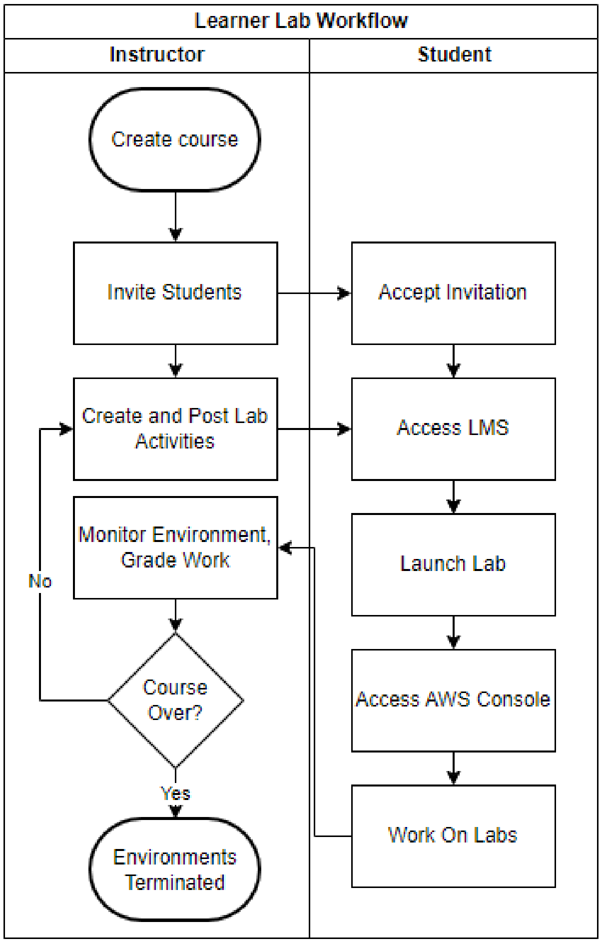


Figure 2 Classroom Management

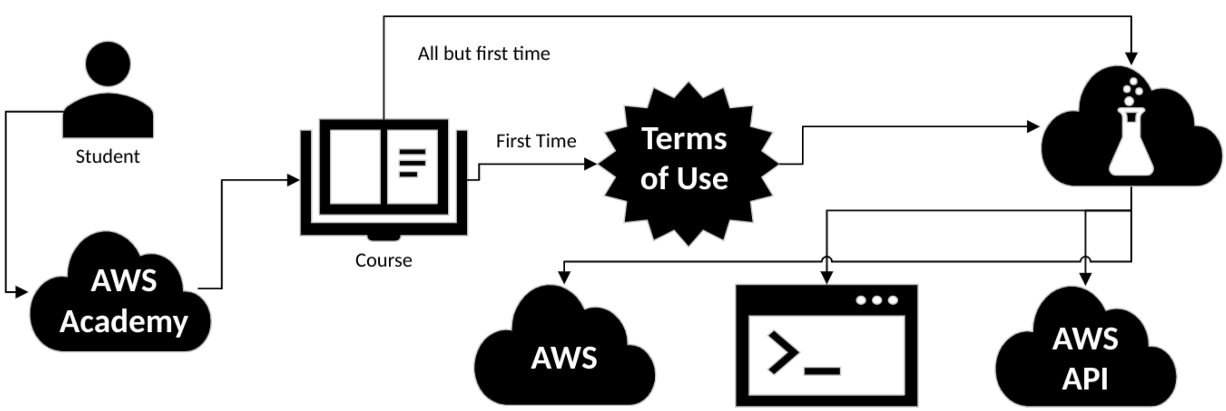
Before inviting students to an AWS Learner Lab environment, instructors should summarize key acceptable use policies before inviting students to a Learner Lab course and ideally require them to pass a quiz on those policies. A quiz (such as the sample in Appendix B) serves as a deterrent control and establishes an audit trail to reinforce the acceptable use policy.

The AWS Academy LMS gives students an acceptable use policy on the first login. Most students scroll to the bottom of the policy and accept it without reading it thoroughly. However, specific uses of the Learner Labs (such as mining cryptocurrency) automatically trigger AWS Academy account deactivation.

If students will be enrolled in several AWS Academy courses, it is a best practice to add students to a single course initially. This approach streamlines the account creation process for new students. Instructors should educate students about the potential confusion surrounding login credentials. Since single sign-on or federation is unavailable, many students mistakenly use their university login credentials instead of their AWS Academy credentials. Students must log in with the invited email, not an alias.

The AWS Management Console (the website for managing AWS resources) uses cookies to maintain session state. Students registered in several AWS Academy Courses or with personal AWS accounts can experience confusion when accessing the Management Console.

Figure 3 Student Workflow



Educators should ensure students confirm the user identity displayed in the Management Console. All Learner Lab accounts will follow the username format "voclabs/user" followed by numbers. Accessing an AWS environment with the wrong account credentials will cause errors. To fix these errors, students must log out of the Management Console and re-launch the Learner Lab from the AWS Academy LMS.

Though the cloud removes nearly all client configuration challenges, ad blockers, privacy tools, and browser cookie settings can interfere with the Learner Lab, requiring some browser troubleshooting after onboarding.

Figure 3 shows a student's process to access AWS services through the Learner Lab course. Following this process, the student will have access to the AWS Management Console in a browser tab in just a few minutes. Students can investigate, configure, provision, and manage cloud resources like working professionals.

Vocareum

Figure 3 Student Workflow

Vocareum is the bridge between AWS Academy LMS and the AWS cloud. When a student enrolls in a Learner Lab course, Vocareum provisions the student's AWS cloud environment with security keys and policies that grant access to many AWS resources. The Vocareum interface allows students to launch their environment, download SSH keys and credentials, access the AWS Management Console, shut down resources, and more.

A significant advantage of the Learner Lab (compared to students running labs on their laptops) is that the Vocareum interface allows instructors to monitor, change, or evaluate student workspaces. Instructors can remotely help students troubleshoot and fix issues.

Persistence

The AWS Academy Learner Lab offers a long-running lab environment suitable for student projects for up to 6 months. However, some resources have specific time limits. For example, Vocareum will shut down, but not delete, Elastic Compute Cloud (EC2) instances four hours after launching a Learner Lab session. Students can extend the session manually if needed. Extending the lab may result in power cycling the running EC2 instances and can change the public IP address. EC2 instances will not automatically be terminated (i.e., deleted) unless abuse is detected. Persistence allows students to keep working where they left off but can create challenges when systems have dependencies that require instances to start in a particular order. Students should set any order-dependent services, such as database clustering, to manually rebuild the cluster in the necessary order.

Learner Lab Service Restrictions

The AWS Academy Learner Lab provides access to a restricted set of AWS services. The AWS Academy Learner Lab Foundation Services Guide documents the specific services and their limitations. For example, some expensive managed services are disabled, EC2 instances cannot be created from a custom Amazon Machine Image (AMI), and students cannot provision virtual machines with many GPUs. The authors have distilled the Lab Foundations Service guide with a recommended set of useful AWS components in Appendix C.

The previous sections provided an overview of getting started with the AWS Academy, creating Learner Lab courses, and starting Learner Lab sessions. The following section describes how educators can use the Learner Lab to teach effectively.

4. PEDAGOGICAL SUGGESTIONS

The Learner Lab supports pedagogical best practices in the cloud. The Learner Lab promotes active learning through hands-on projects and group work. Educators provide opportunities for differentiated instruction by challenging students to extend assignments in novel ways. Educators can use the Learner Lab for formative assessment by inspecting student workspaces to assess comprehension. This section discusses how educators can incorporate pedagogical best practices with the Learner Lab.

Consider the Real-World Impact

Students need context to understand the technology and its importance. Students should explore real-world applications of AWS skills beyond the classroom. When students research cloud computing job opportunities, they gain valuable insights into the relevance and high demand for cloud computing expertise (Chen et al., 2012). This perspective will motivate students to apply themselves to learning cloud computer skills in the Learner Lab because the post-graduation benefits will be clear.

Course Sequencing
Instructors can reap numerous advantages by introducing students to the Learner Lab early in their academic program. Students can acquire the fundamentals of cloud computing early in their degree programs (Woods, 2018; Podeschi & Debo, 2022). They can apply these skills to more complex subjects and real-world situations as they move through their courses. They continue using the Learner Lab to work on projects unique to their courses, practice using AWS services, and review material. Using the Learner Lab in multiple courses reinforces learning, smooths integration, and fosters continuity. By understanding cloud technology through several classes using the Learner Lab, students can see the interactions between various services, pick up best practices, and hone their problem-solving skills. See Appendix D for a sample of course sequencing.

The Learner Lab allows students to leverage knowledge and skills acquired from prerequisite courses. For instance, if Python is included in previous classes, students can use the Learner Lab for serverless computing with AWS Lambda and data analysis with Jupyter Notebooks (Mitri, 2023). Using Python in AWS reinforces students' Python skills. It provides a practical application of these skills within the AWS environment, helping strengthen the Python learned in the prior course and showing its uses in industry.

Moreover, exploring other AWS services that align with the content of different classes is beneficial. For example, if a database course is part of the curriculum, introducing AWS RDS (Relational Database Service) or DynamoDB could provide students with hands-on experience in managing and interacting with databases in the cloud. Similarly, incorporating AWS Amplify or Elastic Beanstalk could be beneficial if a course covers web development.

By integrating AWS services that complement the curriculum, students can see the direct application of their classroom learning in a real-world, industry-standard, industry-leading environment. This approach equips them with valuable skills that are highly sought after in the tech industry and still underrepresented in academic institutions (Chen et al., 2012; Flood & Hall, 2022; Mew & Money, 2018; Milošević et al., 2022; Pike & Brown, 2019).

Learner Lab Onboarding Support
The cloud can be complex and intimidating. The Learner Lab contains short videos that address primary use cases, such as accessing EC2 instances via SSH. However, educators should consider adding additional content, including videos that support the onboarding process. For example, educators might cover such issues as encountering pages that do not load properly or repeatedly accepting terms of service, which are typical in the first-time setup process.

Custom Lab Materials
Amazon constantly updates and expands the AWS cloud. The Learner Lab gives access to the current AWS offerings. Instructor-created lab guides may need to be refreshed periodically. To reduce the maintenance burden, consider leveraging rich media, such as videos, to help students (Goteng et al., 2022; Nasim et al., 2021; Sablić et al., 2021). Students may be better served when encouraged to find helpful videos rather than providing specific ones (Almuslamani et al., 2020).

Building Scaffolded Learning Experiences
Bloom’s taxonomy is one helpful way to think about a student’s learning journey. Students cannot create a solution to a problem until they can remember facts, understand the concepts, apply the information they have learned to new situations, analyze the connections between concepts, and evaluate options for solving a problem (Krathwohl, 2002). Using the cloud gives students access to tools that allow them to create solutions once they are knowledgeable enough within the appropriate domain.

When creating a course, it is suggested that educators use a scaffolded approach. For instance, instructors could create a sequence of projects and tasks that require students to move up the taxonomy, starting with labs that provide step-by-step instructions (*guided labs*), labs that leave some details up to students to figure out (*challenge tasks*), and finally new an original projects that students can create (*independent projects*).

Guided Labs
In Guided Labs students follow step-by-step instructions to complete specific tasks. This approach is beneficial for beginners who are just getting started with AWS services. It allows them to gain a basic understanding and comprehension of the tools and concepts. Guided labs align with the “remember” and “understand” levels in Bloom’s taxonomy. Challenge tasks align with the “apply,” “Analyze,” and “Evaluate” levels of Bloom’s taxonomy.

Challenge Tasks
With challenge tasks educators present students with tasks or problems to solve using the AWS

services using high-level prompts. This approach encourages students to apply their knowledge, analyze solutions, and synthesize information to achieve the desired outcome.

Independent Projects
Educators can assign students to design and implement their projects within the AWS environment. This not only tests students' understanding and application of AWS services but also their ability to evaluate and make judgments about their work and the work of others. At this level, minimal instructions challenge students to solve complex problems, make decisions, and create original solutions. Students find real-world scenarios to do self-initiated project work. This experiential learning helps students see how the learning they have achieved can be applied after graduation. For example, a student used the Learner Lab to test technologies for a master's thesis (Morales Muñoz, 2024). Independent projects align with the "create" level of Bloom's taxonomy.

The Learner Lab supports educators' efforts to teach effectively. Cloud computing is complex. In the following section, we provide technical recommendations that help educators achieve learning outcomes while minimizing technical complexity.

5. LEARNER LAB TECHNICAL BEST PRACTICES

This section contains some best practices we have learned to help educators effectively leverage the technical components of the Learner Lab. Following this guidance, educators new to the Learner Lab can avoid pitfalls and embrace best practices for working with the Learner Lab's features and constraints.

Managing Key Pairs
All AWS customers (including Learner Lab students) are responsible for securing access to resources in the AWS cloud. Students maintain access control lists, passwords, and keys. AWS relies on key pairs–a public key and an associated private key–to secure access to many resources. Students must protect private keys like any other sensitive data. Students can either 1) use the key pairs provided by Vocareum or 2) create their key pairs.

Option 1: Use Vocareum's Key Pair
Vocareum provisions each student's Learner Lab environment with a new key pair. Students download their public and private keys in the Learner Lab LMS. If students lose their key pairs, they can redownload their keys from the LMS. Relying on Vocareum's keys makes it easier for students to maintain access to their resources.

Option 2: Manage Custom Key Pairs
Students can create key pairs using tools like ssh-keygen or the AWS Management Console. If students create their keys using ssh-keygen, they must upload the public key to their AWS Management Console to enable its use. If students lose their custom private keys, they lose access to their resources until they associate new keys with existing resources.

Cost Management
AWS provides students with limited credits without a guarantee that those credits can be increased. Generally, students spend well under their allotted credits. However, a few critical mistakes can increase credit spending substantially. Cost management primarily comprises three practices: service selection, service sizing, and session management.

Manage Cost with Service Selection
Generally, avoid expensive AWS managed services. Some AWS managed services would deplete students' budgets in weeks, even with little to no usage. Instructors should use pricing calculators when developing exercises to anticipate costs. It is sometimes necessary to build scaled-down services that mimic managed services. For example, students can grant EC2 instances internet access in private subnets using manually built network address translation (NAT) instances or implement the AWS-managed NAT Gateway. A NAT instance might cost a few dollars over a semester, whereas the AWS-managed NAT Gateway could consume the student's allotted credits alone.

Many services are free or scale directly with usage. For example, Virtual Private Cloud (VPC), Internet Gateway (IGW), and Simple Storage Service (S3) buckets incur no costs alone. Charges are only incurred for data stored in S3 buckets or EC2 instances created in VPCs.

Manage Costs with Service Sizing
Size EC2 instances as small as possible to achieve an acceptable level of service. A sufficient Linux instance (t3.micro, with two virtual CPUs and a gig of memory) costs a penny per hour. A large Linux instance (t3.2xlarge, with eight virtual CPUs and 32 gigs of memory) costs 33 cents an hour. These costs add up quickly, especially when multiple instances are created and run over a semester.

In one author's class, a student exhausted the Learner Lab credit provided in weeks by oversizing EC2 instances. Also, the student provisioned a new instance each time they got stuck without terminating the previous ones. The student provisioned dozens of large servers instead of a single, small server. In another case, a student showed the faculty member a pricing estimate for the CloudWatch logging that would cost more than USD 100.00 per month. By reducing the number of logged items the learning outcomes were achieved for less than USD 5.00 per month. Instructors can and should monitor lab spending using the Learner Lab's instructor interface, especially early in the term.

Manage Cost with Session Management

Students should actively end their Learner Lab sessions when they finish their tasks rather than wait for Vocareum to put those services to sleep. Keeping labs running can result in unexpected costs, particularly for resources that incur hourly charges. After lab sessions, students should also sign out of the Amazon Web Services Console to avoid Single Sign-On (SSO) issues. Failure to sign out can lead to authentication challenges, hindering student access to resources in subsequent sessions.

Identity and Access Management

The AWS cloud provides fine-grained Identity and Access Management (IAM) control. The Learner Lab restricts access to many IAM features. A lab role that grants access to AWS features is instantiated in each Learner Lab environment and has access to many AWS resources. In some cases the lab role may lack sufficient access to the AWS resources needed to perform a task.

Educators may petition the AWS Academy for more access, but requests to add access may not be approved. Educators must test lab instructions in the Learner Lab because an activity that worked may now require features disabled by IAM policy in the Learner Lab.

Restrict Access to Resources

Instructors must explain how to secure resources. S3 buckets should restrict write access. Strong passwords or private keys should protect EC2 instances. Strong passwords and security policies should secure RDS instances. API endpoints should be managed appropriately. The Learner Lab does not limit external connections to AWS resources. Limiting access falls upon each student. In our experience, hackers have used students' unsecured resources for data exfiltration. Spikes in usage are often evidence of hacker usage in spending on S3, RDS, or EC2. Vocareum may terminate student labs if they detect indicators of compromise. In extreme cases, an entire Learner Lab course may be temporarily disabled, affecting all students in the course.

Following the security principle of least privilege is difficult with Learner Lab IAM restrictions. Due to this limitation and students' lack of understanding of securing resources, additional security measures may be needed. A list of trusted IP address ranges, or an additional approval step to accept and show data from external sources may be used to hinder hackers from using student-developed applications for data exfiltration.

Serverless vs. Infrastructure

Serverless is a paradigm in which software functions are deployed without provisioning or maintaining the servers upon which those functions run. In the Learner Lab environment, serverless architecture avoids problems associated with creating and maintaining EC2 instances. Serverless is a good choice when students need to write code to meet business objectives.

Educators should use the traditional server-based architecture with EC2 instances when learning objectives emphasize infrastructure. Educators can leverage the Learner Lab environment to create web servers, database servers, directory servers, DNS servers, and other servers that mimic traditional data center environments.

Security Groups

The EC2 instance creation workflow defaults to creating a new security group for each instance. Instead of creating a new security group when launching EC2 instances, students should create security groups with meaningful names and descriptions based on EC2 server roles. For example, it might be prudent to have a "Public Web Server" security group that allows inbound traffic in ports 80 (HTTP) and 443 (HTTPS) from the public Internet.

Using consistent naming helps instructors troubleshoot security group problems. For example, Linux web servers might need port 22 open for SSH connections from a private subnetwork. When troubleshooting SSH connectivity to a Linux web server, the instructor could first check that the Linux web server security group was applied to the web server and then check if the security group has the appropriate inbound rules.

Network Segmentation
Network segmentation is a best practice for developing secure and performant networks. In AWS, a VPC can be divided into several subnetworks. Public subnetworks can reach the Internet through an IGW. A sample network diagram is in Appendix E.

Because they lack public IP addresses, EC2 instances in private networks are not granted internet access by default. However, they can connect to other EC2 instances in the same VPC. EC2 instances in private subnetworks cannot receive inbound connections from the internet, which makes administering those instances using Secure Shell (SSH) or Remote Desktop Protocol (RDP) more challenging. AWS Systems Manager allows SSH and remote shell connections to instances in private subnetworks. However, a Windows bastion host is required to connect to private instances using RDP. Bastion hosts are described in the next section.

Bastion Hosts
A bastion host is used as the entry point for administrative purposes into a network. We recommend putting a Linux or Windows Server EC2 instance in a public subnet as the bastion host. We recommend a Windows Server when both RDP and SSH are required.

The bastion host’s security group should allow inbound RDP traffic from anywhere online (0.0.0.0/0). Ideally, the inbound rules would only allow connections from specific IP addresses. However, because student IP addresses change frequently, the recommendation for restricting inbound connections to a particular IP address becomes impractical. AWS provisions EC2 instances with unique, strong passwords. Students must protect the Administrator password and avoid changing it to something weaker, otherwise, the bastion host could be compromised.

NAT instances
NAT instances are virtual machines created in public subnetworks serving as proxies from private subnets to the public internet. AWS officially endorses NAT instances as an alternative to its NAT Gateway managed service. Deploy the NAT instance as a small Amazon Linux EC2 instance in a public subnet. It should automatically obtain a public IP address and have a private IP address assigned statically. Private route tables should be modified to add a default gateway pointing to the NAT instance.

Static Private IP Addressing
By default, AWS assigns private IP addresses to EC2 instances automatically when the instances are provisioned. The IP addresses fall within the range defined by the subnetwork where the instance is deployed. However, two students could deploy instances in their respective private subnets and have instances with different private IP addresses. We recommend specifying a specific private IP address for the EC2 instances when provisioning for guided labs. Setting static private IP addresses helps students and instructors verify connectivity between servers, such as from a web server to a database server in a two-tier architecture.

Application Containerization
Installing applications on Linux can be challenging because software repositories, permissions models, and command-line tools may differ between distributions. Our experience shows that students struggle to follow vendor instructions to ensure their Linux platforms meet application requirements. Application containerization provides an abstraction layer on top of unique Linux distributions. Docker is a common platform for creating, deploying, and managing application containers. It is easier for students to install and deploy a Docker container than installing applications manually. In our experience, teaching students to deploy applications via Docker takes less time than teaching students to install application-specific dependencies and code. Docker has proven to streamline application installation and management (Dubec et al., 2023; Sakshi & Dutta, 2024; Tambi & Shin, 2024).

User Data for Instance Customization
The EC2 launch wizard includes a text area for “user data.” The user data is executed as shell commands, PowerShell scripts, or cloud-init directives when the instance is first initialized. These commands might install specific software, configure services, or set environment variables. For example, an instructor might provide students with a script to automate the entire Apache HTTP Server setup process so that students can start reaching learning objectives with minimal manual setup.

Collectively, these technical best practices have allowed us to create repeatable, effective lesson plans that help students succeed in the Learner Lab.

6. CONCLUSION

The AWS Academy Learner Lab environment is a powerful tool for educators to create realistic, flexible, and scalable learning exercises. Using the Learner Lab, students provision, manage and configure real computing environments.

Institutions must become members of the AWS Academy to leverage the Learner Lab environment. Instructors must complete asynchronous training to teach AWS Academy courses. Instructors should make students aware of key elements of the acceptable use policy as part of the course enrollment process, such as the prohibitions against mining cryptocurrency, storing sensitive data, or using the environment for commercial purposes.

Lab exercises should avoid paid managed services, stick with recommended services (Appendix C), and provide clear guidelines for security resources. Throughout a course, educators should monitor students' environments. As with all learning platforms, the Learner Lab has its learning curve. We hope that the guidance in this paper helps educators avoid pitfalls and start teaching effectively using the Learner Lab environment.

7. REFERENCES

Almuslamani, H. A. I., Nassar, I. A., & Mahdi, O. R. (2020). The Effect of Educational Videos on Increasing Student Classroom Participation: Action Research. *International Journal of Higher Education*, *9*(3), 323–330. https://doi.org/10.5430/ijhe.v9n3p323

Brereton, E. (2022, April 26). How Higher Ed Institutions Are Meeting the Demand for Student Devices. *EdTech*. https://edtechmagazine.com/higher/article/2022/04/how-higher-ed-institutions-are-meeting-demand-student-devices

Chen, L., Liu, Y., Gallagher, M., Pailthorpe, B., Sadiq, S., Shen, H. T., & Li, X. (2012). Introducing Cloud Computing Topics in Curricula. *Journal of Information Systems Education, 23*(3), 315–324.

Correia, E., & Tasker, S. (2022, April 27). The Cloud, the Curriculum and the Classroom: The Case of AWS at one Public Tertiary Institution. *Proceedings of the 12th Annual CITRENZ Conference 2021.* 12th Annual Conference of Computing and Information Technology Research and Education New Zealand(CITRENZ 2021) & 34th Annual Conference of the National Advisory Committee on Computing Qualifications, New Zealand.

Dubec, J., Balažia, J., Bencel, R., & Čičák, P. (2023). Docker-Based Assignment Evaluations in E-Learning. *2023 Communication and Information Technologies (KIT)*, 1–5. https://doi.org/10.1109/KIT59097.2023.10297093

Flood, D., & Hall, A. (2022). Application of Amazon Web Services within teaching & learning at Coventry University Group. *Proceedings of the 6th Conference on Computing Education Practice*, 25–28. https://doi.org/10.1145/3498343.3498350

Goteng, G. L., Shohel, M. M. C., & Tariq, F. (2022). Enhancing Student Employability in Collaboration with the Industry: Case Study of a Partnership with Amazon Web Services Academy. *Education Sciences, 12*(6), 1–18. https://doi.org/10.3390/educsci12060366

Krathwohl, D. R. (2002). A Revision of Bloom's Taxonomy: An Overview. *Theory Into Practice, 41*(4), 212–218. https://doi.org/10.1207/s15430421tip4104_2

Merchante, L. F. S., Vallez, C. M., & Szczerbik, C. (2024). Towards a low-cost universal access cloud framework to assess STEM students. *arXiv*. https://doi.org/10.48550/ARXIV.2401.17701

Mew, L. (2016). Information Systems Education: The Case for the Academic Cloud. *Information Systems Education Journal, 14*(5), 71–79. https://isedj.org/2016-14/n5/ISEDJv14n5p71.pdf

Mew, L., & Money, W. (2018). Cloud Computing: Changing Paradigms for Information Systems Development Service Providers and Practitioners*. Journal of Information Systems Applied Research, 11*(3), 35–47.

Meyer, L., Jr., & Billionniere, E. (2021). AWS Academy vs Microsoft Learn for Educators vs IBM Skills Academy: The Educators Choice. *Proceedings of the Society for Information Technology & Teacher Education International Conference*, 528–534. https://www.learntechlib.org/primary/p/219180/

Milošević, M., Bogićević, Ž., & Ristić, O. (2022). Implementing the AWS Academy curriculum into a cloud computing course. *Proceedings TIE 2022*, 278–282. https://doi.org/10.46793/TIE22.278M

Mitri, M. (2023). Using Python and AWS for NoSQL in a BI Course. *Journal of Information Systems Education, 34*(1), 41–48. https://jise.org/Volume34/n1/JISE2023v34n1pp41-48.html

Moltó, G., Naranjo, D. M., & Segrelles, J. D. (2020). Insights from Learning Analytics for Hands-On Cloud Computing Labs in AWS. *Applied Sciences, 10*(24), 1–13. https://doi.org/10.3390/app10249148

Morales Muñoz, E. S. (2024). Containerization of a Pentesting Platform [Master Thesis, Universitat Politècnica de Catalunya]. http://hdl.handle.net/2117/410522

Murphy, M., & McClelland, M. (2009). My Personal Computer Lab: Operating in the "Cloud." *Information Systems Education Journal, 7*(93), 3–11. http://isedj.org/7/93/

Nasim, S., Siddiqi, Z., & Shamshir, M. (2021). Impact Of Video-Based Learning Websites On Students' Academic Performance. *International Journal of Scientific & Technology Research, 10*(04), 336–342.

Nwokeji, J., Roldan, M., Soltys, M., & Holmes, T. (2021). A Hands-on Approach to Cloudifying Curriculum in Computing and Engineering Education. *2021 IEEE Frontiers in Education Conference (FIE)*, 1–3. https://doi.org/10.1109/FIE49875.2021.9637137

Pike, R., & Brown, B. (2019). IT Infrastructure Strategy in an Undergraduate Course. *Information Systems Education Journal, 17*(5), 17–21. https://isedj.org/2019-17/n5/ISEDJv17n5p17.pdf

Podeschi, R., & DeBo, J. (2022). Integrating AWS Cloud Practitioner Certification into a Systems Administration Course. *Information Systems Education Journal, 20*(5), 17–26. https://isedj.org/2022-20/n5/ISEDJv20n5p17.pdf

Qasem, Y. A. M., Abdullah, R., Jusoh, Y. Y., Atan, R., & Asadi, S. (2019). Cloud Computing Adoption in Higher Education Institutions: A Systematic Review. *IEEE Access, 7*, 63722–63744. https://doi.org/10.1109/ACCESS.2019.2916234

Sablić, M., Mirosavljević, A., & Škugor, A. (2021). Video-Based Learning (VBL)—Past, Present and Future: an Overview of the Research Published from 2008 to 2019. *Technology, Knowledge and Learning, 26*(4), 1061–1077. https://doi.org/10.1007/s10758-020-09455-5

Sakshi, S., & Dutta, N. (2024). A Large-Scale Empirical Study Identifying Practitioners' Perspectives on Challenges in Docker Development: Analysis Using Stack Overflow. *International Journal of Innovative Research in Computer and Communication Engineering, 12*(2), 1104–1111. https://doi.org/10.15680/IJIRCCE.2024.1202064

Segec, P., Moravcik, M., & Kontsek, M. (2021). Cloud education – the first AWS Academy in Slovakia. *2021 19th International Conference on Emerging ELearning Technologies and Applications (ICETA)*, 339–344. https://doi.org/10.1109/ICETA54173.2021.9726602

Tambi, V. K., & Singh, N. (2024). A Comprehensive Empirical Study Determining Practitioners' Views on Docker Development Difficulties: Stack Overflow Analysis. *International Journal of Innovative Research in Computer and Communication Engineering, 12*(1), 157–164. https://doi.org/10.15680/IJIRCCE.2024.1201073|

Woods, D. (2018). Introducing the Cloud in an Introductory IT Course. *Information Systems Education Journal, 16*(1), 13–20.

Appendix A: Key Terms and Definitions

AWS Academy – An educational program that provides a cloud computing curriculum combined with practical learning experiences to educational institutions.

AWS Management Console – A web-based graphical user interface that allows users to monitor, configure, and manage cloud services.

Bastion Host – A secure server placed in a public-facing network to act as an access point for managing systems within a private network.

Cloud Computing – An information technology model that enables users to compute power, storage, and applications without relying on local hardware.

CloudFormation – A service that automates the setup and management of cloud resources using predefined templates.

Containerization – A method of packaging software and its dependencies into a standardized unit, ensuring it runs consistently across different environments.

Docker – A tool that enables the deployment of applications in lightweight, portable environments called containers, improving consistency across systems.

Elastic Compute Cloud (EC2) – A service that provides resizable virtual servers to run applications in the cloud.

Elasticity – The ability of a cloud system to adjust to demand by scaling resources to match.

Identity and Access Management (IAM) – A security framework that manages user permissions and access to cloud resources.

Infrastructure as a Service (IaaS) – A cloud model where virtualized computing resources such as storage, networking, and servers are provided on demand.

NAT Gateway/NAT Instance – A service that enables instances in a private network to access the internet while preventing inbound traffic from external sources.

Platform as a Service (PaaS) – A cloud model that provides developers with a managed environment to build, deploy, and manage applications without physical infrastructure.

Private Subnet – A segment of a network that is isolated from direct internet access used for securing internal systems.

Public Subnet – A network segment allowing resources to communicate directly with the internet.

Security Groups – Configurable rules that define allowed and restricted traffic for cloud-based virtual machines and services.

Serverless Architecture – A computing model where applications run in the cloud without requiring users to manage the underlying infrastructure.

Serverless Computing – A cloud-based execution model where applications scale automatically, and users are only billed for the resources they consume.

Simple Storage Service (S3) – A scalable cloud storage solution allowing users to store objects and retrieve them virtually anywhere.

Software as a Service (SaaS) – A cloud model where applications are maintained by a third party and accessed through the web, eliminating physical infrastructure and the need for skilled people to maintain the software.

SSH Key Pair – A pair of cryptographic keys used for securely authenticating access to cloud-based systems and services.

Virtual Machine (VM) – A software-based simulation that represents a physical computer.

Virtual Private Cloud (VPC) – A logically isolated network within the cloud where users can define and manage their networking configurations.

Appendix B: Sample Onboarding Quiz Questions

Sample Onboarding Quiz Question 1
By providing your email address below, you certify that you will **not** use the AWS Educate Learner Lab to:

- Mine cryptocurrency
- Run for-profit services
- Host sensitive data (e.g., data subject to GDPR or HIPAA)

In addition, you will comply with the AWS Acceptable Use Policy and the AWS Responsible AI Policy. You recognize that a violation of these policies could result in AWS account deactivation and university discipline.

Your email: ____________________

Sample Onboarding Quiz Question 2 (Answers are bolded.)
Please check the boxes next to activities that are **prohibited** in the AWS Learner Lab environment:

- Creating virtual machines
- **Mining cryptocurrency**
- Deploying sample websites for training purposes
- Uploading randomized test data to a database
- **Storing sensitive data (e.g., data subject to GDPR or HIPAA)**
- **Running for-profit services**
- Creating public and private subnetworks

Sample Onboarding Quiz Question 3 (Answers are bolded.)
If the Learner Lab, or piece in it will not function what are some common reason why and how to troubleshoot them **(Please select the most correct answer)**

- The browser still has the session for a prior lab and is confused. Just need to log out of AWS and click to get in again.
- The terms of use needs to be accepted. Click on the link to get into where you can launch the lab again
- All of a specific resource has been used. Example you can only have 10 EC2 Instances running.
- Your lab has suspicious activity and is getting stopped. Look at the billing dashboard and see what prices are going up. Look to see how that service may be used by others in a nefarious way. Secure the service. You may also want to review logs and current system activity.
- All of the accounts funds have been used for the assignment or the course
- **All of the answers are correct**

Appendix C: Key Learner Lab AWS Components

The AWS cloud offers a vast array of services. This section summarizes our recommendations for using these services based on our experience up to March 2025 using the AWS Learner Lab. As the Learner Lab is constantly updating, you should review the documentation as to what is available and can be used, including the limitations put on those services.

AWS Component: Simple Storage Service (S3)
Related Endorsed Services: Amazon S3 Select, Glacier
Shut down when lab session ends: No
Example Classroom Activities: Host a website, store backup files, store data for ML training, serverless application
Security Concerns: Secure S3 buckets to restrict write access from the Internet. Only allow read access from the Internet if required.
Helpful Resources:
Video - https://www.youtube.com/watch?v=P3xR3Fzezp8
Guide - https://docs.aws.amazon.com/AmazonS3/latest/userguide/WebsiteHosting.html

AWS Component: Elastic Compute Cloud (EC2)
Endorsed: Yes
Related Endorsed Services: Elastic File Storage (EFS), Elastic Block Store (EBS), Security Groups, Elastic Load Balancer (ELB), Auto Scaling Groups, Systems Manager (SSM), Amazon Machine Images (AMIs), Parameter Store, Elastic Beanstalk
Shut down when lab session ends: Yes
Example Classroom Activities: OS administration, application (installation, configure, maintain, secure), web application development, web server, scaling/clustering
Security Concerns: Key management, application passwords, patching
Helpful Resources:
Video - https://www.youtube.com/watch?v=1ueohGEr-14
Guide - https://docs.aws.amazon.com/AWSEC2/latest/UserGuide/option3-task1-launch-ec2-instance.html

AWS Component: Lambda
Related Endorsed Services: Application programming interface (API) gateway, DynamoDB, S3, Simple Notification Service (SNS), Simple Queue Service (SQS), Step Functions, CloudWatch, CloudTrail, Parameter Store
Shut down when lab session ends: No
Example Classroom Activities: Intro to programming, microservices, form processing, data processing and manipulation, API creation
Security Concerns: Due to the inability to use IAM, services need to be secured by other means if both accepting and displaying the accepted data. Least privilege should be implemented to the extent that it can. Inputs should be validated. Cross-Origin Resource Sharing (CORS) will need authorization
Helpful Resources:
Video - https://www.youtube.com/watch?v=fQ8Q_wWusYo
Video - https://www.youtube.com/watch?v=_s_tbELNFQs
Guide - https://docs.aws.amazon.com/lambda/latest/dg/getting-started.html

AWS Component: VPC
Related Endorsed Services: EC2, Relational Database Service (RDS)*, Security Groups, Network Access Control Lists (ACL), Subnetting, Availability Zones, ELB, Auto Scaling Groups
Shut down when lab session ends: No
Example Classroom Activities: Networking, subnetting, troubleshooting connectivity, service hardening, service deployment
Security Concerns: To secure services, we advise that security groups be as specific as possible

AWS Component: Cloud9
Related Endorsed Services: Cloud Formation, Command Line Interface (CLI), Code Wisperer

Shut down when lab session ends: Yes
Example Classroom Activities: Development, Infrastructure Automation
Security Concerns:

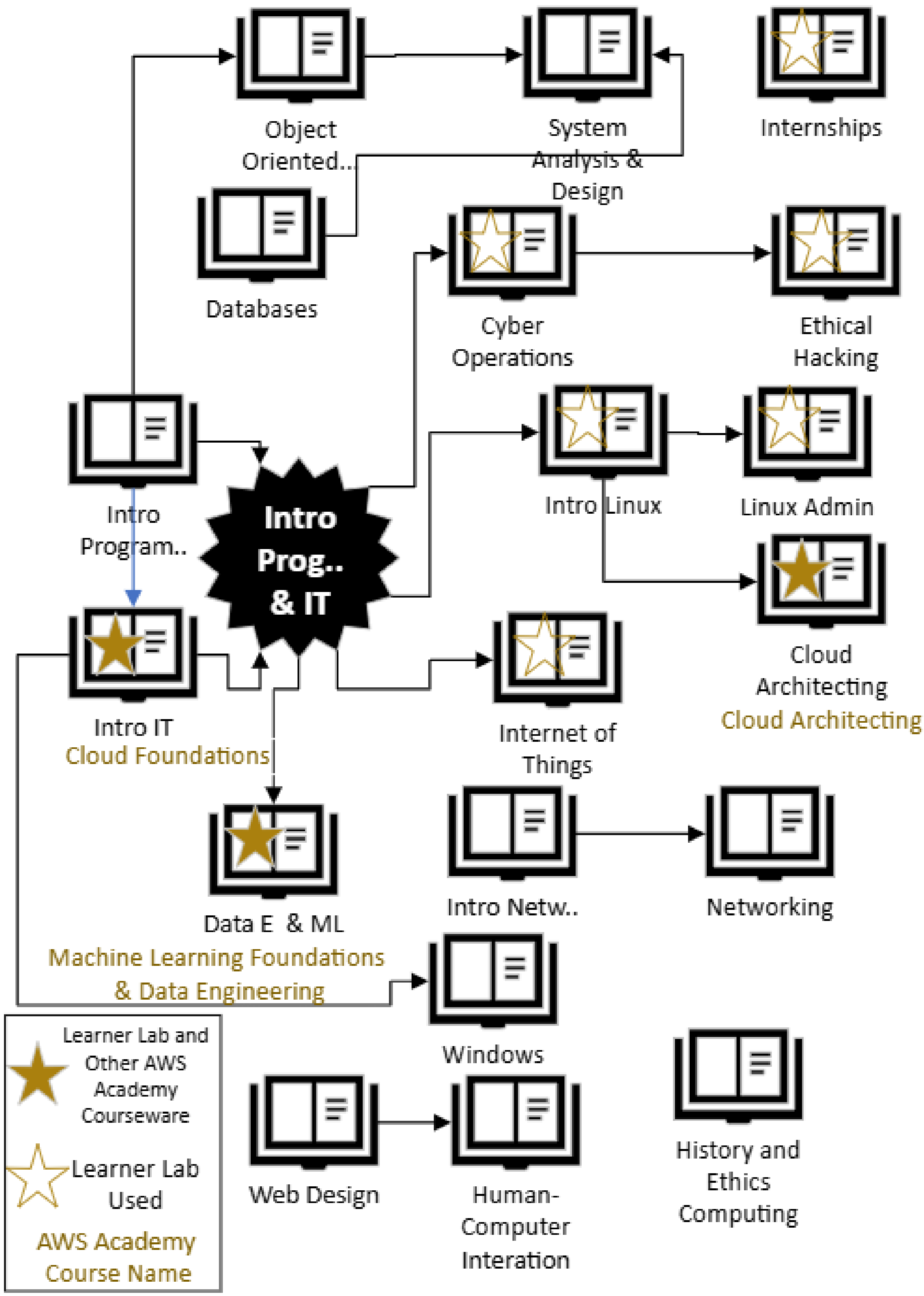
AWS Component: SageMaker
Related Endorsed Services: S3, Glue, S3 Select, Athena, Lambda, Jupyter Notebooks, Step Functions, Aurora, Code Wisperer, Data Pipeline, Elastic MapReduce (EMR), Kinesis
Shut down when lab session ends: Yes
Example Classroom Activities: Data Engineering, Extract Transform and Load Data, Use data in Data Analysis or Machine Learning
Security Concerns: Data should rarely be open to the world

AWS Component: Elastic IP
Shut down when lab session ends: No
Example Classroom Activities: Web hosting, server management, service hosting
Concerns: Charged when in and not in use. If assigned to an EC2 that shuts down when the lab ends you will get charged for the IP address. This can quickly add up over a semester. Use caution when using Elastic IP addresses.
Helpful Resources:
Video - https://www.youtube.com/watch?v=lJNtk0G4VCA
Guide - https://docs.aws.amazon.com/AWSEC2/latest/UserGuide/elastic-ip-addresses-eip.html

AWS Component: Instance Store
Shut down when lab session ends: Yes
Example Classroom Activities: Clustered systems local storage
Concerns: Should not be used on instances where data should survive reboot as the storage does not survive reboot. Storage is not persistent.

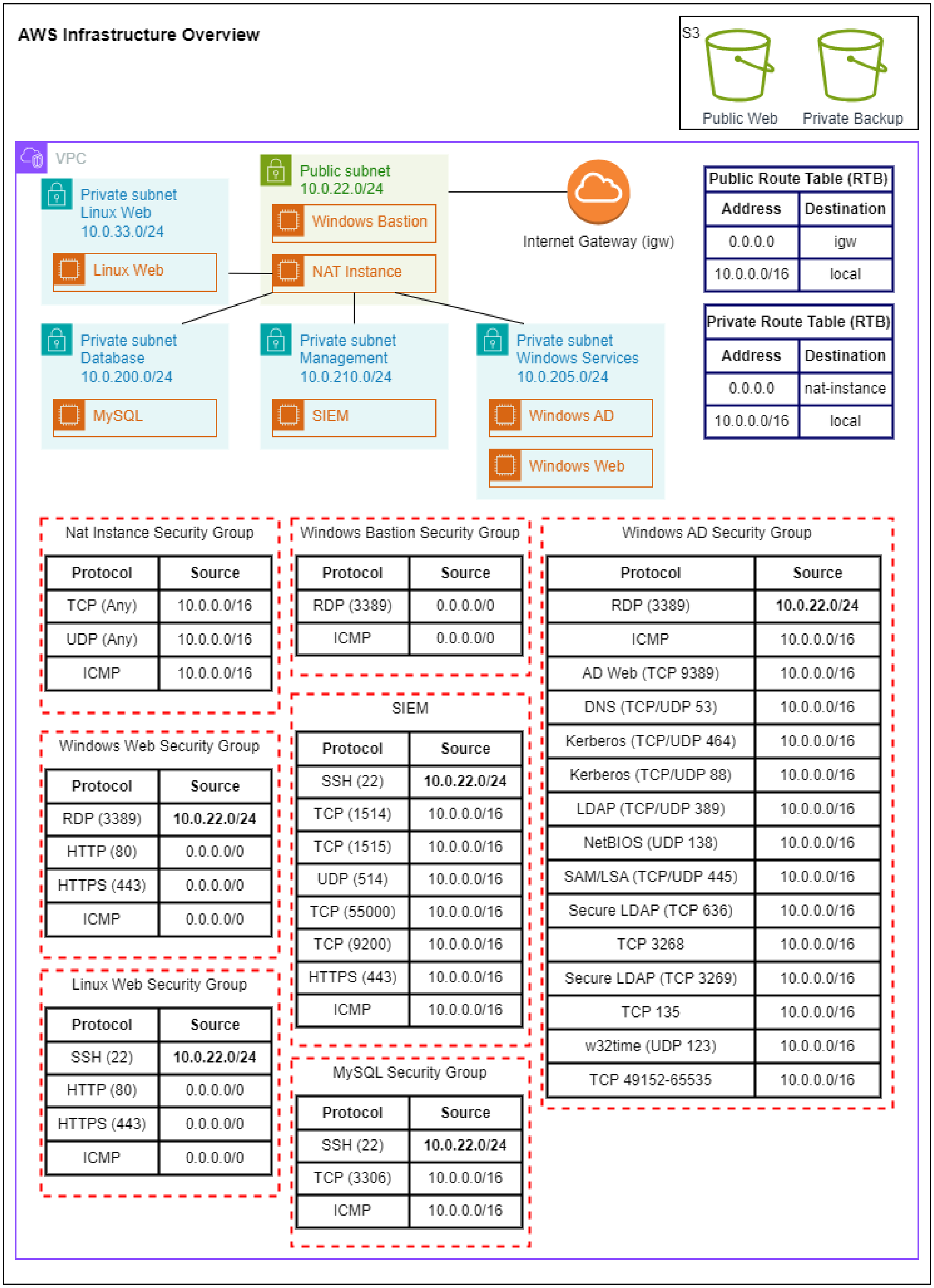
AWS Component: Lightsail
Shut down when lab session ends:
Example Classroom Activities: Pre configured lightweight applications for easy usage
Concerns: May shortcut some of the learning objectives of many courses.

Appendix D: Sample Course Sequencing



Appendix E: Sample Network Diagram

Below is a sample network diagram that shows how a cloud environment could be set up for learning exercises.



Public Route Table (RTB)

Address	Destination
0.0.0.0	igw
10.0.0.0/16	local

Private Route Table (RTB)

Address	Destination
0.0.0.0	nat-instance
10.0.0.0/16	local

Nat Instance Security Group

Protocol	Source
TCP (Any)	10.0.0.0/16
UDP (Any)	10.0.0.0/16
ICMP	10.0.0.0/16

Windows Bastion Security Group

Protocol	Source
RDP (3389)	0.0.0.0/0
ICMP	0.0.0.0/0

Windows AD Security Group

Protocol	Source
RDP (3389)	**10.0.22.0/24**
ICMP	10.0.0.0/16
AD Web (TCP 9389)	10.0.0.0/16
DNS (TCP/UDP 53)	10.0.0.0/16
Kerberos (TCP/UDP 464)	10.0.0.0/16
Kerberos (TCP/UDP 88)	10.0.0.0/16
LDAP (TCP/UDP 389)	10.0.0.0/16
NetBIOS (UDP 138)	10.0.0.0/16
SAM/LSA (TCP/UDP 445)	10.0.0.0/16
Secure LDAP (TCP 636)	10.0.0.0/16
TCP 3268	10.0.0.0/16
Secure LDAP (TCP 3269)	10.0.0.0/16
TCP 135	10.0.0.0/16
w32time (UDP 123)	10.0.0.0/16
TCP 49152-65535	10.0.0.0/16

SIEM

Protocol	Source
SSH (22)	**10.0.22.0/24**
TCP (1514)	10.0.0.0/16
TCP (1515)	10.0.0.0/16
UDP (514)	10.0.0.0/16
TCP (55000)	10.0.0.0/16
TCP (9200)	10.0.0.0/16
HTTPS (443)	10.0.0.0/16
ICMP	10.0.0.0/16

Windows Web Security Group

Protocol	Source
RDP (3389)	**10.0.22.0/24**
HTTP (80)	0.0.0.0/0
HTTPS (443)	0.0.0.0/0
ICMP	0.0.0.0/0

Linux Web Security Group

Protocol	Source
SSH (22)	**10.0.22.0/24**
HTTP (80)	0.0.0.0/0
HTTPS (443)	0.0.0.0/0
ICMP	0.0.0.0/0

MySQL Security Group

Protocol	Source
SSH (22)	**10.0.22.0/24**
TCP (3306)	10.0.0.0/16
ICMP	10.0.0.0/16

Intelligence of AI: Investigating Artificial Intelligence's Ability to Detect Itself

Brian Clements
baclem6488@ung.edu

Tamirat T Abegaz
tamirat.abegaz@ung.edu

Bryson Payne
bryson.payne@ung.edu

University of North Georgia
Dahlonega, GA 30597

Abstract

The rise of artificial intelligence (AI) has made life and work easier; however, AI has also made it almost impossible to determine whether the information we consume is legitimate, AI-generated, or AI-manipulated. This paper examines how the use of artificial intelligence, specifically GPT-4, Gemini Advanced, and Claude Opus, can aid a user in identifying whether a work was created by a human or artificial intelligence. These three models will be evaluated by receiving datasets of human-created and AI-generated text documents, images of nature, images of manmade objects, and images of art. This work will investigate which model, if any, could be an effective tool to aid in preventing misinformation.

Keywords: ChatGPT, Gemini, Artificial Intelligence, Large Language Models, Multimodal Models.

Recommended Citation: Clements, B., Abegaz, T.T., Payne, B., (2025). Intelligence of AI: Investigating Artificial Intelligence's Ability to Detect Itself. *Information Systems Education Journal. v23*, n6, pp 37-43. DOI https://doi.org/10.62273/WAFS1445

Intelligence of AI: Investigating Artificial Intelligence's Ability to Detect Itself

Brian Clements, Tamirat T. Abegaz and Bryson Payne

1. INTRODUCTION

Concerns about AI span a wide range, from its potential use for academic dishonesty to the threat it poses to both blue-collar and white-collar jobs, and even the fear of a Terminator-like apocalypse. Regardless of the specific issue, artificial intelligence has rapidly become a contentious topic in both academic circles and industry discussions. One of AI's most significant capabilities is its ability to produce highly detailed and realistic fakes. These AI-generated imitations can be found in various contexts, including social media, political advertisements, and educational settings, leading individuals to question the distinction between what is genuine and what is AI-generated or manipulated content.

One way in which artificial intelligence is routinely used is to create believable text responses to virtually any question or query. This can lead to problems such as academic dishonesty, the spreading of misinformation, the creation of phishing emails, and more. In this age of artificial intelligence, it is crucial that humans can distinguish whether a text was created by AI or by a student, journalist, or other credible source.

This research evaluates how humans could use the artificial intelligence models of GPT-4, Gemini Advanced, and Claude to distinguish between human-generated and AI-generated text or images, as well as which characteristics reveal that a piece was created using artificial intelligence. Furthermore, this paper will compare how well these particular AI models distinguish authorship of text compared to human judges.

For this research, it is imperative to understand the workings of multimodal large language models, or MLLMs. As the name suggests, multimodal large language models are based on the concept of large language models which, are computer models that can read, interpret, and respond to human input in a similar manner as a human (Chang and Wang et al., 2024). This form of computer system creates an environment where the computer acts, or at least attempts to act, in the most human-like way possible. An example of this form of system would be an AI chatbot that helps you navigate an online shopping site because it takes the input of the user and responds in a way that makes the user feel as if another human is guiding them. In the simplest terms, multimodal large language models take the concept of traditional large language models, but they incorporate the ability to either take input from various modes, such as images, texts, videos, or audio files, and produce responses in different modes or some combination of the four (Karwa, 2023).

The ability to process and even produce information in these various formats makes MLLMs much more powerful than their text-only predecessors. For this research, the AI models of GPT-4, Gemini Advanced, and Claude will be examined. These three models are known as the most cutting-edge models available to the public at this current time, so this ensures that the research is examining artificial intelligence at the best level possible for the study. These three models are also the top models created by their respective companies, so they will match up very well for comparisons of their power.

The research team predicts that all three AI models, GPT-4, Gemini Advanced, and Claude, will perform better at identifying whether the text pieces were written by humans or AI-generated when compared with the assessments of the human judges. The researchers also predict that out of the three models, GPT-4 will outperform Gemini Advanced and Claude and be able to correctly identify authorship the best.

2. RELATED WORK

The research presented in this paper is the natural successor of a small but growing number of recent studies into detecting AI. In a paper titled "Anomaly Detection: Identifying AI-Generated from Student-Created Pieces", the researchers investigated how well professors could identify whether text-based documents that covered their area of expertise were written by a human author or generated using artificial intelligence (Clements et al., 2023). This study presented professors with two responses to an assignment that would typically be found in their own class, and these responses were one of the following: both written by the student researcher, both generated using AI, or some combination of the two. This ensured a random presentation of documents to the professors. This paper will utilize 20 of the responses found in this previous study to compare how humans did at identifying authorship of text documents with the abilities of GPT-4, Gemini, and Claude.

While considerable attention has been given to the use of AI to grade assignments (Lui et al., 2024) and to digest and tag knowledge (Moore et al., 2024), more recent research has continued in the path noted above in detecting the use of AI in written assignments. Bhattacharjee and Liu (2024) investigated whether ChatGPT could detect AI-generated text by focusing on solving a specific aspect of a word problem and deriving the rest of an answer from that solution. The current research expands this work by testing both text and images across three of the leading AI engines.

There have been multiple studies conducted to test the effectiveness of GPT-4, a newer MLLM from OpenAI based on its prior successful models like ChatGPT. For an example of its power, the technical report of GPT-4 describes how when given a simulated bar exam, GPT-4 scored in the top 10% of all test takers while ChatGPT 3.5 scored in the bottom 10% of scores (OpenAI, 2023, Dash et al., 2014). The same report describes how to test its true capabilities, GPT-4 was asked to complete multiple common exams such as AP exams, the LSAT, and GRE exams, and the researchers state that "GPT-4 exhibits human-level performance on the majority of these professional and academic exams" (OpenAI, 2023, p. 6; Bouafif et al., 2024). Again, GPT-4 appears to be the new standard for how an artificial intelligence model should behave. It is supposedly more human-like than ever. Furthermore, GPT-4 could effectively evaluate images. In its technical report, researchers presented GPT-4 with an image of a VGA plug charging an iPhone, and GPT-4 was able to walk the user through why this is not possible and how it does not make sense that a piece of modern technology would be charging using this rather outdated form of cable (OpenAI, 2023). This ability to effectively evaluate images as well as comprehend intense exams intended for highly intelligent humans makes GPT-4 an extremely powerful tool (Poldark, et al., 2023).

Another study was conducted that compared GPT-4, Bard (the predecessor to the more modern Gemini), and Claude (Borji and Mohammadian, 2023). This study excelled in the use of a set of 1,002 questions about various subjects from simple math to much more complicated topics (Borji and Mohammadian, 2023). One particularly relevant section of this study showed that all three models performed relatively well and similarly at identifying proper grammar, spelling, and definitions of large words (Borji and Mohammadian, 2023). This may hint that these models will perform well at identifying the creator of the text pieces because AI-generated text documents are more likely to have proper grammar and style. One drawback of this study is that it utilized the models in their infancy before they had the capabilities they have now. For example, this study was conducted before GPT-4 had the ability to create images, and Gemini was still its weaker counterpart Bard. Including these updated models will allow this paper's study to add relevant information to the conversation started by Borji and Mohammadian.

3. METHODOLOGY

The goal of this research is to identify which of the models, GPT-4, Gemini Advanced, or Claude is the most powerful through the means of asking the models to identify the creators of various written works and images. This study also will compare the results of the written works with the results found in a previous study performed by the research team to create a comparison on how well these platforms compare to humans. The research team chose to investigate all three of GPT-4, Gemini Advanced, and Claude for this study because they are currently seen as the top AI models. GPT-4 and Gemini Advanced are premium versions of their respective models, ChatGPT 3.5 and Gemini, that are locked behind a paid prescription. Furthermore, Claude Opus is seen as a top-of-the-line tool that is the premium version of the standard Claude Sonnet.

GPT-4 and Gemini Advanced were chosen because of their ability to produce and respond to text as well as images. Claude was chosen because of its great ability to analyze images as well as texts. Although Claude cannot create its own images, it will still be valuable to identify authorship. This allows the researcher to submit both documents and images directly to the models. The first step of this research will be obtaining these models. After the models are obtained, the researcher will feed various works into the models and perform data collection and analysis on what the AI models predict about authorship.

This experiment utilized a total of 4 different data sets with 10 to 20 pieces in each set. Each set contains at least 5 to 10 human-created responses and 5 to 13 AI-generated responses. The data sets are made up of 2 broad categories, text and images. Both of which will be described in detail below.

The text responses make up 20 total works that were submitted to the artificial intelligence models. These responses are as they sound, text pieces that are anywhere from 1 to multiple paragraphs in length. These text pieces were taken from the previous study by this researcher so the results can be compared with the human responses of that study. Seven out of the 20 responses will be pieces that were created by the user. These seven pieces are from subjects such as kinesiology, computer science, environmental science, and more. The diverse texts enable the researcher to identify if there is a particular type of writing for which the AI models struggle to identify the author or maybe genres for which the AI excels in identifying the source. The other 13 text-based pieces were created utilizing the AI models themselves. Some pieces were taken exactly as they were after the initial creation prompt, while some works underwent additional modifications such as "create a grammatical or spelling error" or "lower the reading level of this work" and more, known as prompt engineering (Saravia, 2022). This allowed the research team to gain insight into how artificial intelligence responds to works that are not perfect and that have issues, such as grammatical issues, that may be common in a work that a human would create. Every text-based piece was created by ChatGPT 3.5 and then Bard was given the prompt to "create a piece as humanlike as possible". Again, it will be interesting to see if by asking the AI to produce a "humanlike" piece, the AI models fool themselves when it is then fed to them.

4. IMPLEMENTATION

To collect data for this research, it was vital that the various pieces were input into the AI models of GPT-4, Gemini Advanced, and Claude in a particular manner. One thing the research team noticed was that when a work was put in and the authorship of it was questioned, the models did not always give a clear answer, as if it was hesitant to have an opinion. To combat this, every piece was input utilizing a prompt that is like the following: "the researcher is conducting an experiment and considering the following…." was this piece made using AI or a human? you must choose one." An example of this prompt is found below. This prompt appeared to trick the AI into providing a definite and confident answer.

Also, when it comes to input, the research team needed to ensure that the models focused on the content of the materials especially when given the art pieces and the text pieces, so the research team had to ensure that the AI was told to look at content. Furthermore, to prevent any possibility of bias when predicting the authorship of a piece, a random sequence generator was used, and the pieces were numbered 1 through 20 for text responses, 1 through 10 for the art responses, and the pieces were submitted to each AI model in the same random sequence.

The first method was for text-based responses which involved submitting the documents straight into the models. This method forces the artificial intelligence to evaluate the piece including formatting. The research team still asked the artificial intelligence to act as if it were in an experiment and asked it to give a clear answer about the work's authorship. Like the implementation of the text documents described in the paragraph above, the images were simply uploaded into the various models' prompts. The user was routinely required to persuade the AI that it was participating in an experiment, so it would give a definite answer on who or what created the piece in question. Occasionally, additional coercion was required for the models to provide a definite answer.

5. RESULTS

For this paper, all results were measured using a True Positive (+, +), True Negative (+,-), False Positive (-,+), and False Negative (-,-) scale. True Positives were responses that correctly identified an AI-generated piece as being created using artificial intelligence. On the opposite spectrum, True Negatives were pieces that are predicted to be generated by a human when they were made by a human. False Positives represent when a piece was falsely labeled as AI-generated when in fact it was human-made. Similarly, False Negatives were when pieces that were AI-generated were falsely assumed to be created by a human. Both True Positives and True Negatives represent successful trials for the subjects while False Positives and False Negatives represent errors.

Figure 1 shows the first results obtained from the text data set. This was the only test that included feedback from humans in the results so a comparison could be made between human and AI ability to detect authorship. Surprisingly to the research team, GPT-4 was more effective at detecting AI-generated pieces than humans. Moreover, in effectiveness, humans performed better than AI. Humans had seven true positives and 6 true negatives. Humans also had just one false positive and six false negatives. GPT-4 excelled with eight true positives, but it lacked in every other category with just two true negatives. It also had five false positives and five false negatives. GPT-4 was the only model that came even close to the effectiveness of the human subjects. However, GPT-4 has shown that it would still be an unreliable tool for the detection of text documents due to its alarmingly high number of false positives and negatives. Furthermore, this data showed that Gemini and Claude are practically useless as detection tools for AI-generated text documents.

Analysis Comparison

Metrics	GPT-4	Gemini Advanced	Claude Opus	Humans
True Positive (+,+)	8	1	1	7
True Negative (+,-)	2	5	4	6
False Positive (-,+)	5	2	3	1
False Negative (-,-)	5	12	12	6

Figure 1. Results of the experiment involving text documents with AI and human responses

Figure 2 shows the outcome of the test utilizing images of nature. This data was the result of asking GPT-4, Gemini, and Claude to determine authorship of images of animals as well as natural landscapes. When it came to this test, Claude very obviously outperformed both GPT-4 and Gemini. Out of the 20 total data images, Claude had six True Positives, of which the second highest was only two, and nine True Negatives. Claude finished with one False Positive and four False Negatives. Far from Claude's performance, the second best, if one can even say that performer was GPT-4. This model had just 2 True Positives and the Truest Negatives with 10. This model fell short with its eight False Negatives.

Finally, the worst performer was Gemini. This model struggled with only correctly identifying one true positive and seven True Negatives. It had three False Positives and nine False Negatives. One thing to notice is that GPT-4 and Gemini both appeared to be extra cautious when predicting an AI author with both only choosing AI a total of six times out of 40 combined trials. For some reason, these two models lean heavily towards human authorship even if it is an incorrect guess. On the other hand, Claude was more confident in its abilities and guessed AI authorship a total of seven times out of its 20 trials. Another interesting thing to note is that no AI-generated image was identified as AI by all three models. Only two images were correctly identified by more than one AI: GPT-4 tagged two images as AI, and those two were among six identified by Claude, as shown in Figure 2 below.

Image Analysis Comparison

Metrics	GPT-4	Gemini Advanced	Claude Opus
True Positive (+,+)	2	1	6
True Negative (+,-)	10	7	9
False Positive (-,+)	0	3	1
False Negative (-,-)	8	9	4

Figure 2. Results of the experiment involving images of nature

Figure 3 shows test results involving the images of manmade objects was very interesting. Compared to the other tests, all models appeared to perform relatively well at this task. GPT-4 was the leader again with a total of eight true positives and a perfect 10 true negatives while only misidentifying two of the AI-generated pieces as human work. The next top performer was Gemini which had a total of five true positives and seven true negatives. Gemini struggles on eight pieces where three were misidentified as false positives and five as false negatives.

Bringing up the rear, although not too far behind the other two models is Claude. Claude had just three true positives with a high 9 true negatives. Claude also had one false positive and a total of seven false negatives. All three models appeared to find it easier to identify human-made pieces as such as only four total times a human-made piece was falsely mistaken to be AI. This appears to be a continuing trend as with all data sets, the models typically leaned to identify works as human-made. It was quite surprising that for manmade objects Claude performed worse than natural objects where it was the best at identifying authorship. While on the other hand, GPT-4 and Gemini performed much better at identifying the creator of the manmade works compared to the natural images.

Manmade/Unnatural Images Analysis Comparison

Metrics	GPT-4	Gemini Advanced	Claude Opus
True Positive (+,+)	8	5	3
True Negative (+,-)	10	7	9
False Positive (-,+)	0	3	1
False Negative (-,-)	2	5	7

Figure 3. Chart of results from the experiment involving manmade images

Lastly, Figure 4 shows the test results for the data that represents art will be examined. Quite frankly, all AI models performed horrendously in this test. Paintings and art were chosen purposely by the research team as a dataset because the research team believed it would be extremely difficult for the AI to distinguish between art created by humans by that created by AI; however, the results were even worse than the research team imagined. All three models performed nearly equally poorly. Gemini and Claude had the same results with only one true positive and five true negatives. They then had four false negatives each. GPT-4 had five true negatives and five false negatives. These results show that when it came to art and images of paintings, the models were extremely reluctant to presume an AI author. It appears as if the models just automatically defaulted to human creator for all pieces of this nature. This raises the question of whether the models could tell the human pieces were made by humans or if these were only correct because the models automatically chose human every single time. This trail shows that artificial intelligence appears to be a while from being able to truly identify art as human or AI-generated.

Art/Painting Images Analysis Comparison

Metrics	GPT-4	Gemini Advanced	Claude Opus
True Positive (+,+)	0	1	1
True Negative (+,-)	5	5	5
False Positive (-,+)	0	0	0
False Negative (-,-)	5	4	4

Figure. 4. Results for images involving art.

6. CONCLUSION

Although the research team created a starting point for evaluating multiple AI models' ability to detect AI-generated works, it is simply a starting point. Some limitations need to be discussed for future research into this idea. One area this study lacked was the size of the data sets. The experiment used diverse data sets; however, there were simply not enough, and in the future, it would be preferable to expand this experiment with much larger data sets across dozens (or, by that time, perhaps hundreds) of AI models. This would help limit any bias that may be present in a smaller data set. Although, based on the results shown, it appeared to have little to no effect on the conclusions made by the models, future research should produce AI-generated data samples with a model that is not being observed in the study. This too could limit bias between the models' responses.

GPT-4 performed like a premium AI in three out of four of the tests. As shown in the charts above, in both tests involving text documents and manmade images, GPT-4 performed better than Gemini and Claude. However, when it came to the natural images and the art tests, GPT-4 performed poorly. In terms of use, GPT-4 was one of the easiest models. It rarely ever asked a user to provide more information before revealing its decision. It also was correct most of the time when it was describing what was present in the images regardless of whether it knew who created the images or not. One of the only drawbacks found during this experiment was that at one-point GPT-4 did require the user to wait about two hours before most questions could be asked to the model.

During this study, Gemini performed very average. In every experiment, it was always in the middle on accuracy. It never performed better than any of the other models. This does not mean it is a bad model, it is just not the greatest for the tests conducted in this study. Gemini had a few major drawbacks. One was that it had to constantly be coerced to answer when asked to choose human-made or AI-generated. Constantly, Gemini would say that more information is needed or that it cannot decide, so the research team would have to repeatedly state that it must give an answer. Furthermore, another drawback that was noticed was that although it may be able to identify authorship, Gemini did not always understand what it was even looking at. For example, the image below shows how Gemini says that the image of steak on pasta is a natural landscape with mountains, lakes, and a boat. This begs the question of how well the model processes the content of images, or if it just makes the best guess, it can.

Throughout the study, Claude performed moderately well. It was the most effective model when it came to natural images; however, when it came to manmade images, texts, and art pieces it was around average and performed similarly to Gemini. Like GPT-4, Claude was relatively easy to coerce into giving its opinion on the creator of the work and it required little to no extra questioning for an answer to be provided. Claude had two major drawbacks. The first was that in a series of questions, Claude only allowed a user to submit five images before a new chat must be created. This made keeping all of its information in 1 place impossible. The biggest drawback to

Claude was its limited question space. Even with a $20 monthly price tag, the research team was only able to submit about 12 questions to the model every five hours. This made using Claude extremely frustrating. Due to this reason, the research team believes that GPT-4 is a better option at the same monthly subscription cost of $20.

Although this study showed that no current AI model can effectively determine whether a piece was created by artificial intelligence or not with 100% accuracy, its findings are still meaningful for the future. As models continue to progress, there will continue to be an uprise of deep fakes, and these malicious works show no sign of stopping soon. With, tools and AI models should still be used by humans despite their inaccuracies as simply a guide to provide further information to the humans' own opinions about a piece. If used as a tool to add information to the bigger picture and not as the final word, AI models could still prove effective as identifiers of deep fakes.

7. REFERENCES

Anthropic (2023). Claude Documentation. Retrieved June 4, 2024 from https://docs.anthropic.com/.

Anthropic (2023). Claude Opus. Retrieved May 5, 2024 from https://www.anthropic.com/claude.

Bhattacharjee, A., Liu, H. (2024). Fighting Fire with Fire: Can ChatGPT Detect AI-generated Text? *SIGKDD Explor. Newsl. 25* (2), 14–21. https://doi.org/10.1145/3655103.3655106

Borji, A., Mohammadian, M. (2023). Battle of the WordSmiths: Comparing ChatGPT, GPT-4, Claude, and Bard. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4476855.

Bouafif, M. S., Zheng, C., Qasse, I. A., Zulkoski, E., Hamdaqa, M., & Khomh, F. (2024). A Context-Driven Approach for Co-Auditing Smart Contracts with The Support of GPT-4 code interpreter. arXiv preprint. https://doi.org/10.48550/arXiv.2406.18075.

Chang, Y., Wang, X., Wang, J., Wu, Y., Yang, L., Zhu, K., ... & Xie, X. (2024). A survey on evaluation of large language models. *ACM Transactions on Intelligent Systems and Technology*, *15*(3), 1-45.

Clements, B., Abegaz, T., Payne, B. (2024) Anomaly Detection: Distinguishing AI-Generated Works from Student-Created Submissions. *Proceedings of the International Academy of Business Disciplines 2024.* Las Vegas, NV. April 4-6, 2024.

Conte, N. (2024). Ranked: The most popular ai tools. Visual Capitalist.

Dash, D., Thapa, R., Banda, J. M., Swaminathan, A., Cheatham, M., Kashyap, M., ... & Shah, N. H. (2023). Evaluation of GPT-3.5 and GPT-4 for supporting real-world information needs in healthcare delivery. *arXiv preprint*. https://doi.org/10.48550/arXiv.2304.13714

Google. (2024). Gemini Advanced. Retrieved March 3, 2024 from https://gemini.google/advanced/.

Karwa, S. (2023) Exploring Multimodal Large Language Models: A Step Forward in AI. Retrieved March 25, 2024 from https://medium.com/@cout.shubham.

Liu, T., Chatain, J., Kobel-Keller, L., Kortemeyer, G., Willwacher, T., & Sachan, M. (2024). AI-assisted Automated Short Answer Grading of Handwritten University Level Mathematics Exams. *arXiv preprint.* https://doi.org/10.48550/arXiv.2408.11728

Moore, S., Schmucker, R., Mitchell, T., & Stamper, J. (2024). Automated Generation and Tagging of Knowledge Components from Multiple-Choice Questions. In *Proceedings of the Eleventh ACM Conference on Learning@ Scale*. Association for Computing Machinery, New York, NY, USA, 122–133. https://doi.org/10.1145/3657604.3662030

OpenAI. (2023). GPT-4. Retrieved March 31, 2024 from https://chat.openai.com.

OpenAI. (2023). GPT-4 Technical Report. arXiv.org. https://doi.org/10.48550/arXiv.2303.08774

Poldrack, R. A., Lu, T., & Beguš, G. (2023). AI-assisted coding: Experiments with GPT-4. arXiv.org. https://doi.org/10.48550/arXiv.2304.13187

Saravia, E. (2022). Prompt Engineering Guide. Retrieved April 2, 2024 from https://www.promptingguide.ai/

Utilizing GPTZero to Detect AI-Generated Writing

Karen Paullet
paullet@rmu.edu

Jamie Pinchot
pinchot@rmu.edu

Evan Kinney
kinney@rmu.edu

Tyler Stewart
stewartty@rmu.edu

Computer Information Systems Department
Robert Morris University
Moon Township, PA 15108 USA

Abstract

Generative AI tools such as ChatGPT are now in widespread use and are often utilized by students to help in creating writing assignments intended to be written entirely by the student. This has spurred the need for AI detection tools such as GPTZero. This study sought to determine the accuracy of GPTZero's AI detection in identifying whether writing was created by a human, generated by AI, or a mix of both. Because many students now submit work that is a mix of both their original writing and AI-generated text, it has become more important to be able to accurately identify mixed-generated writing. The study analyzed 500 writing samples of human, AI, and mixed origin and utilized GPTZero's Deep Analysis to identify writing origin sentence-by-sentence in the mixed samples. Results from this study indicated that GPTZero accurately identified the writing origin of all samples, within an 89% to 93% accuracy rate of mixed-generated writing, and a 95-99% accuracy of writing that was written by a human or entirely by AI.

Keywords: artificial intelligence, GPTZero, ChatGPT, plagiarism detection, large language models, generative AI, plagiarism

Recommended Citation: Paullet, K., Pinchot, J., Kinney, E., Stewart, T., (2025). Detecting AI-Generated Writing Using GPTZero. *Information Systems Education Journal* v23, n6 pp 44-52. DOI# https://doi.org/10.62273/PZWW7741

Utilizing GPTZero to Detect AI-Generated Writing

Karen Paullet, Jamie Pinchot, Evan Kinney and Tyler Stewart

1. INTRODUCTION

Generative AI large language models such as ChatGPT (OpenAI, 2023) can be used to create high quality human-like written work including papers, letters, reports, essays, resumes, song lyrics, poems, slide decks, answers to questions, and even computer code. The applications of ChatGPT are endless (Sadasivan, 2024) and continue to be explored. The rate by which these tools are being adopted, especially by students, is quite rapid (Johnston et al., 2024; Kyaw, 2023; Nam, 2023).

The widespread use of these AI tools can create many conveniences and productivity benefits for writers, but it also creates risks of misuse in terms of data security, intellectual property, and ethics. The potential for misuse includes generating fake news, fake product reviews, or otherwise manipulating web content for social engineering (Sadasivan, 2024). Ethical concerns are especially relevant in the academic environment where unauthorized use of AI for a student assignment constitutes academic cheating or plagiarism (Adeshola, 2023; Zhang et al., 2024; Sadasivan, 2024).

In some cases, the use of generative AI tools for assignments in an educational setting may be allowed, or even encouraged, by instructors in order to incorporate these new tools into students' learning experiences (Tossell et al., 2024). After all, once students enter the workforce, they will be expected to have AI literacy (Ng, 2021).

However, there are still situations when AI-tools will not be allowed for writing assignments; For instance, when the student is required to write original research, or original creative content such as a short story or poem, or is learning a writing technique or grammar. In these and other situations, the learning goals of an assignment will not be met if a student is assisted by AI. So, it has now become an issue for educators to be able to identify when student writing is original, and when it has been generated by AI.

Studies have shown that there are many difficulties for human evaluators in distinguishing between text that has been written by a human and text that has been generated by AI (Casal & Kessler, 2023; Liu et al., 2024). Traditional plagiarism detectors have also been found to be unreliable in detecting AI-generated text (Lo, 2023).

Thus, there was a need for a new class of AI detection tools that can detect whether text has been AI-generated (Zhang et al., 2024). However, many AI detection tools have been reported to be inaccurate, noting a high number of false positives (Steponenaite & Barakat, 2023; D'Agostino, 2023). Notably, OpenAI, the creator of ChatGPT, stated that AI detectors "have not been reliable enough given that educators could be making judgments about students with potentially lasting consequences" (OpenAI, 2024).

Because AI detection tools are in their infancy and little is known about whether the results provided by these tools are accurate and can be trusted, further study of them is required. One of the most popular AI detection tools is GPTZero (GPTZero.me). This tool was selected for study by the researchers to further analyze its' accuracy. The study explores the following research question:

RQ1: How accurate are GPTZero's detection methods in determining if text was written by a human, artificial intelligence or a combination of both?

2. LITERATURE REVIEW

The use of AI in education provides new opportunities and challenges for both students and educators. It has caused mixed feelings among educators, as some view it as an opportunity for advanced teaching and learning while others focus on the drawbacks which include plagiarism, generation of incorrect information, and biases in data training (Baidoo-Anu & Ansah, 2023; Rasul et al., 2023).

Rasul et al. (2023) identified five benefits of the use of AI in higher education, which include: personalized feedback for students, facilitation of adaptive learning, support for research and data analysis tasks, development of more innovative assessments, and automation of administrative services. The authors also identify five challenges, including: academic integrity concerns, issues with reinforcement of skills sets for graduates, reliability issues, problems with assessing learning outcomes effectively, and potential biases. They argue that educators must approach the use of AI tools such as ChatGPT for academic purposes with caution in order to ensure responsible and ethical use.

Plagiarism in academia continues to be an issue that has only gained new complexities as generative AI has grown in popularity. There are challenges associated with human evaluation of writing to determine whether it is AI-generated or written by a human (Cassal & Kessler, 2023; Liu et al., 2024).

Cassal and Kessler (2023) recruited 72 reviewers and 27 editors for academic journals and had each participant complete a judgment task to determine whether paper abstracts were human or AI-generated. Though the reviewers employed a variety of techniques to judge the writing samples, they only correctly identified 38.9% of the writing that was generated by AI. Further, the study identified varying beliefs by the editors in regard to whether or not there are ethical uses of AI tools for academic research (Cassal & Kessler, 2023). Liu et al. (2024) studied 155 faculty members, researchers, and graduate students to see if they could correctly identify writing samples that were generated by AI. The overall accuracy rate for detection by the participants in the study was 48.82%. This accuracy rate is slightly worse than random guesses (Liu et al., 2024).

In response to this issue, a number of software tools have been developed to counteract and detect AI-generated work. One of these tools is the OpenAI classifier, created by the developers of ChatGPT, which achieved 26% accuracy in a test conducted by Elkhatat et al. (2023). Another tested tool was Copyleaks, which can integrate with several key Learning Management Systems and APIs. Interestingly, this tool yielded a 99% accuracy when identifying AI-generated writing. To evaluate these tools, Elkhatat et al. (2023) utilized ChatGPT to create two 15-paragraph writing samples. To diversify the sample pool, 5 sets of human-created samples were factored in. The result ended up being that each tool has a variable difference in accuracy for identifying AI-generated writing samples. The most notable facet of this result is that the complexity of delineating human and AI-generated writing is becoming increasingly difficult. This can clearly be observed as some of the text searching tools to check for AI-generation in writing cannot detect it (Elkhatat et al., 2023).

In another analysis of AI-generated writing detectors, 16 publicly available tools were tested to observe their accuracy rates. An initial review of the 16 tools found that GPT – 2/RoBERTa, TurnItIn, and ZeroGPT were the most consistently accurate. It is important to note, however, that there was a lack of consistency across the analyses. Seventeen analyses ran undergraduate writing or short responses while the remaining 10 analyses utilized a variety of text such as abstracts, admissions essays, and exam essays (Walters, 2023). In order to successfully test the 16 tools, a sample set of documents was created. Of this sample set, 42 short papers were generated via ChatGPT. Another set of 42 documents were pulled from the Manhattan College English course 110 to add a low-level human-generated text sample (Walters, 2023). To evaluate the writing samples, the outputs of the detectors were collected and classified based on key characteristics such as whether there were numeric values in the text, whether the wording was casual or formal, and what degree of confidence was present in the writing. The results indicated that 2 of the 16 detectors correctly identified the human or AI-generated status of the documents with no incorrect or uncertain responses: Copyleaks and TurnItIn. Among the remaining detectors, it is notable that the accuracy was fairly high, ranging around 63-88% (Walters, 2023).

Liu et al. (2024) developed a deep learning-based detection tool called CheckGPT to determine whether any given text snippet was generated by ChatGPT. They conducted a benchmarking text with 2.385 million samples of human-written and ChatGPT-written writing. Some of the samples were also not fully written by ChatGPT, but were completed or edited by ChatGPT (from writing started by a human). Results showed that CheckGPT is "highly accurate, flexible, and transferable" (Liu et al., 2024, p. 13).

Sadasivan et al. (2024) found that while some AI detectors can be accurate for basic detection, there are methods that can be used to fool the detectors into a false positive result. They develop a recursive paraphrasing attack that can be applied to text written by AI that can break a number of AI detectors. In particular, this technique can be effective in hiding AI-generated text from retrieval-based detectors and also tools that use watermarking schemes, neural networks, and zero-shot classifiers.

However, one of the most popular AI detectors, GPTZero, claims to already be implementing detection for specific paraphrasing models and maintains an updated 'greylist' of bypasser methods, which they claim to patch within days of identification (Tian, 2023). Based on its' popularity as well as these claims in regard to accuracy, the researchers chose the GPTZero AI detection tool to explore for this study.

How Does GPTZero Work?
In January of 2023, online software called GPTZero, developed by Edward Tian and Alex Cui, was launched as a response to concerns about AI-generated material (Tian, et al., 2024). GPTZero is an AI detector which checks to see if a document was created using a large language model such as ChatGPT. GPTZero detects AI on sentence structure, paragraph, and document level. GPTZero detects if tools such as ChatGPT, GPT3, Google-Gemini, LLAMA, or newer AI models were used to create a document or if it was written by a human (Tian, et al., 2024). The accuracy of GPTZero continues to increase as more texts are submitted to the model. "By learning from existing generative AI models, the tools calculate and predict the probability of words in an AI-generated sentence" (Shrivastava, para 4, 2023). GPTZero analyzes patterns of writing using syntax and sentence length to identify text created by machine learning.

GPTZero uses seven machine learning components to determine the probability of the use of AI in text: Education Module, Burstiness, Perplexity, GPTZeroX, GPTZero Shield, Internet Text Search and Deep Learning (Tian, et al., 2024). Each component provides a weighted score to the Document Classification and Document Breakdown that calculates an estimation of the amount of human-generated, AI-generated or mixed-generated writing that has been used. The Education component runs the input text against other human-written text created by students. The Burstiness component analyzes the text to see if there are patterns in the writing, whereas Perplexity determines which words might come after one another. GPTZeroX is a component that is able to provide sentence-by-sentence classifications for human-generated, AI-generated, and mixed-generated text. GPTZero Shield defends against other tools looking to exploit the AI detector. The Internet Text Search component analyzes direct quotes from existing websites through May 2023 at the time of this writing. Lastly, the Deep Learning component is used to detect the usage of AI. Human-generated text is continuously fed into GPTZero so that it is constantly learning patterns to help determine the likelihood of AI produced material. The model is trained from creative writing, scientific writing, blogs, news articles, and more. The submissions are tested against a large-scale dataset of human- and AI-generated material (Tian, et al., 2024).

GPTZero provides three options to analyze documents. Users can copy and paste text from a source directly into GPTZero. Second, users can upload documents that are in Microsoft Word or other applications directly into GPTZero. Lastly, users can use Origin Google Chrome and Microsoft Word extensions which provide direct analysis while creating a document or reviewing a website (Tian, et al., 2024).

GPTZero has both paid and unpaid subscription plans. The tool works the same regardless of the plan used. The difference between the two versions is the number of characters that can be scanned by GPTZero. The free version only allows for seven submissions per day, limited to 5000 characters for each submission. GPTZero tracks the IP address to determine if the limit has been reached regardless of which browser is being used. In addition to the free version there are three paid subscription plans. The Essential Plan allows users up to 150,000 words per month which is equivalent to 300 pages of scanning. The Premium Plan allows 300,000 words per month which would include 600 pages of scanning to include the AI deep scanner and is multilingual. Lastly, the Professional Plan allows for 500,000 words equivalent to 1000 pages of text, everything listed above, and allows for 10,000,000 words overage and military grade data security (Tian, et al., 2024). All three versions use the same model to detect if text was written by a human, AI or a combination of human and AI. Each gives a breakdown for detecting the use of AI in written material with descriptions of the results.

Deep Analysis Explained
Using Deep Analysis is a feature of GPTZero which allows for a more comprehensive breakdown of the text. When scanning text, GPTZero has an output which indicates the percent of text written by a human, the percent generated by AI and will also show a percentage for a mix of human- and AI-generated content. GPTZero provides an overall probability of AI use and highlights which sentences are likely to be AI-generated. Deep Analysis quantifies the impact that each sentence makes on the overall AI probability in the writing.

3. METHODOLOGY

GPTZero claims to have a 99% accuracy rate compared to its competitors such as Originality and ZeroGPT (Tian, et al., 2024). In order to test the 99% accuracy rate, the researchers created an experiment using their own writing samples and analyzed it using GPTZero. The human samples were created from the authors' own writings prior to the creation of artificial intelligence tools such as ChatGPT in November of 2022. The artificial intelligence samples were created by using ChatGPT and Claude. The authors developed samples on numerous IT topics with word counts ranging from 500-words to 1000-word papers. After creating the samples, the authors uploaded the work to ChatGPT or Claude to rewrite the samples using AI. The mixed samples were created by using a combination of the authors' writing that was not used in the human samples and AI created samples. Due to the size limitations of the free version of GPTZero, the researchers purchased the Professional Plan which allows 500,000 words of scanning. In order to test the validity of the researchers' samples, a pilot test was first conducted. Researcher A created a sample of 20 papers. The papers were created using prior work written by the research team.

The 20 papers that were created included 6 written by a human, 7 generated using AI, and 7 that were a mix of human- and AI-generated text. The samples were numbered 1 through 20 and were then given to Researcher B to run through GPTZero. The papers given to Researcher B were anonymous and only displayed numbers. Researcher B had no idea of the origin of each paper. After running the 20 papers through GPTZero, Researcher B compared the results from the blind test to those of the known test with Researcher A's information. The 6 papers that were human-generated and the 7 papers created by AI resulted in a 98% accuracy rate with a 2% false positive rate. The results of the 7 papers that had a mix of human- and AI-generated material had an accuracy rate of 70%. The researchers realized that the reason for the percentages being off by 30% had to do with the word count in the document. When the documents that had a mix of AI and human writing were copied into the document, there were numerous font sizes. The researchers were essentially guessing the percentage instead of taking the overall word count of the document and dividing it by the percentage of AI writing and the percentage of human writing. This lesson learned from the pilot was then corrected and implemented in the current study.

In addition to the 20 papers created for the pilot, the researchers conducted a preliminary study where 100 unique samples were created correcting the issues from the pilot test (Paullet, et.al, 2024). Results from the 100 samples were used as a comparison for this study in which 500 additional samples were created to analyze using GPTZero.

The writing samples for both the preliminary 100-sample study (Paullet, et.al, 2024) and the current study of 500 samples were created using the same method as the pilot test. Researcher A created 168 human samples from work written by the authors prior to November 30, 2022, 167 samples were created using AI tools ChatGPT or Claude, and 165 samples were created combining both human and AI writing. However, in the current study, the researchers additionally utilized Deep Analysis to analyze the text line by line, highlighting which text was written by a human and which it identified as written by AI. A deep analysis was not done on the initial 100 sample study. Instead, the researchers only looked at the percentage output of whether the sample was created by a human, AI or a mix of both (Paullet, et.al, 2024). The deep analysis used in the current study provides additional insight into understanding how GPTZero identifies mixed-generated text.

The 500 writing samples created by Researcher A were anonymized and numbered 1 through 500 and put into a Microsoft Excel spreadsheet. The samples were then given to Researcher B to run through GPTZero. GPTZero allows for a single document to be uploaded or numerous documents at one time. Researcher B uploaded the 500 documents at one time and ran a report showing the results of the experiment. A deep analysis/scan was run on all of the samples to see if GPTZero could identify line-by-line which text was written by a human, generated using AI, or contained a mix of both human and AI content. The results were then compared with the known writing origin of the samples. The results of this study are discussed below.

4. RESULTS

This study tested the functionality and accuracy of GPTZero in identifying human-generated, AI-generated, and mixed-generated text utilizing 500 unique writing samples in October2024. The research question for this study was:

RQ1: How accurate are GPTZero's detection methods in determining if text was written by a human, artificial intelligence or a combination of both?

All (100%) of the 500 samples were correctly identified, matching the known writing origin of each sample, and indicating that GPTZero accurately identified all human-generated, AI-generated, and mixed-generated samples. The number of samples created for each type is shown in Table 1.

Sample Type	Number Created
Human	168
AI	167
Mix of Human & AI	165

Table 1: Breakdown of samples created

The initial analysis of the samples identified which samples were written by a human, AI, or a mix of both. Table 2 lists the results of the unknown samples run through GPTZero by Researcher B compared to the known samples created by Researcher A. Of the 168 human samples, 167 showed a 99% chance of being written by a human and 1 sample had an output of 95-98% chance of being written by a human. The 167 AI-generated samples showed a 99% percent chance of being created using AI in 163 of the samples. Four of the samples resulted in a 95-98% chance of being AI-generated. Having a 95-98% accuracy rate even on the four samples is extremely high and shows validity. The final set of results were for samples where a combination of both human writing and writing created using AI were combined. There was a total of 165 mixed samples. Of the 165 samples that had both AI and human content, 106 had a 99% accuracy for the samples created by Researcher A. For example, one of the samples created had a 65% accuracy of the writing being human and 35% created by AI, GPTZero was able to determine the breakdown within 1% of which sentences were human written and which were created by AI. The percentages in the known sample were calculated by taking the total number of words in the document divided by the number of words written by a human and then the total number of words in the document divided by the AI created content to determine the percentages of the sample. GPTZero provides a line-by-line breakdown where it indicates which sentences were most likely created by a human, which were generated by AI and which are a combination of both. There was a total of 165 mixed samples of human and AI content in which 106 samples had a 99% accuracy rate, with 43 of the samples showing a 95-98% accuracy rate, and 16 samples more than 5%. The 16 samples that showed an accuracy rate of more than 5% were examined further. It is interesting to note that the 16 samples that showed an accuracy rate higher than 5% had sentences that were intertwined in the writing of the same paragraph. Even with the writing going back and forth from human to AI, only 7 of the samples were actually over 10% (90% accuracy rate) with the highest being a 19% percent difference from the unknown to the known. Even at 81% it yielded a high enough result showing what was human-generated compared to AI-generated. As a comparison, faculty use Turnitin, a tool used to combat plagiarism. If Turnitin yielded an 81% match to work written by others one would determine that a students plagiarized the work. This outcome should do the same as it pertains to AI created content.

Sample Type	Number Created	1%	2-5%	More Than 5%
Human	168	167	1	0
AI	167	163	4	0
Mix of Human & AI	165	106	43	16

Table 2: Comparison of GPTZero's identification of writing origin to known writing origin of samples

The results of the current 500 sample study are very comparable to the results of an earlier study conducted using only 100 samples (Paullet et.al, 2024). In both studies, GPTZero was 100% able to accurately identify if a sample was created by a human, AI, or a mix in all samples created. Additionally, none of the 100 samples from the previous study yielded anything lower than 82% accuracy rate and that was only in two samples where sentences of human created content and AI generated content were intertwined. This means that a sentence written by a human and then an AI generated sentence going back and forth. The other 98 samples were within 95-100% accuracy comparing the known to the unknown. The current study of 500 samples yielded similar results. Figure 1 shows how the data was broken down in GPTZero after a document has been scanned for detection in July 2024. The output is color coded where orange is the probability of being AI generated.

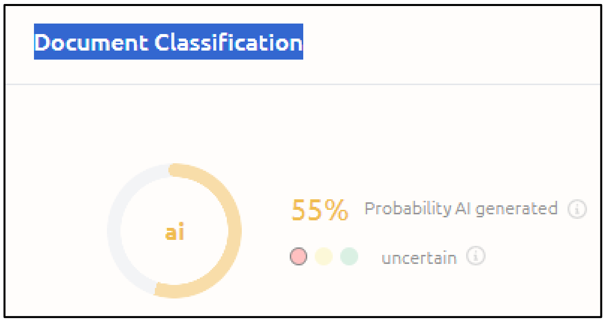


Figure 1: GPTZero Document Classification

Figure 2 is the probability breakdown of the sample showing what percentage was written by a human, AI or mixed after running it through GPTZero in July 2024. The human created content is green, the mixed of AI and human generated content is blue and the AI generated content is orange.

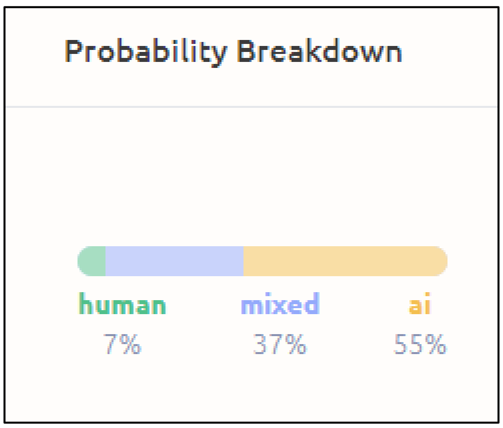


Figure 2: GPTZero Probability Breakdown

The current study of 500 samples delved deeper into the scans to see if GPTZero was able to actually detect sentence-by-sentence what was created by a human and what was created by AI or a combination of both. There were 165 samples that were written with a combination of human and AI that were analyzed using the Deep Scan. In all 165 of the samples, GPTZero was able to detect sentence-by-sentence what was human-generated and what was generated by AI. In 142 samples, GPTZero was almost 90% accurate while the remaining 23 samples had a 93% sentence-by-sentence accuracy rate. The Deep Scan highlights the top sentences driving the probability of AI and the top sentences driving the probability of being written by a human. Figure 2 shows a probability breakdown of being 7% created by a human, 55% AI generated and 37% is a mix of human and AI generated content. GPTZero highlights the document in different colors and provides a score along with an explanation on why it detects each probability sentence-by-sentence. "The per-sentence breakdown quantifies how much each sentence contributes to the model's overall AI probability score. Higher scores mean greater impact on the model's prediction" (Tian, et al., 2024). The deep scan explains the highlighting colors used by GPTZero. For instance, green highlighting implies more human-like content whereas orange highlighting implies more AI-like content. The user can then hover over each highlighted line to get a more detailed prediction of the content.

5. DISCUSSION

The results of the study answer the research question indicating that GPTZero accurately identified the writing origin of all samples, within an 89% to 93% accuracy rate of mixed-generated writing, and a 95-99% accuracy of writing that was written by a human or entirely by AI. GPTZero is a reliable tool in detecting AI generated writing and can be an important tool for educators to use in classes where students are required to submit original writing without the use of AI.

There are tools claiming to be able to by-pass AI detectors. The creators of GPTZero have tested one of the AI by-pass detection tools. The result of their study that paraphrasing detection is very possible and GPTZero has already implemented tools to detect if paraphrasing of AI generated text can still be detected into the software (Tian, 2023, para 2).

Artificial intelligence is not going away. As educators, it is important to embrace the technology and find strategies that can help to eliminate misuse of AI in the classroom. Students must be taught about the risks of using AI and learn how to express themselves in their writing. They must still be able to communicate when AI is not available. Below are tips that can be utilized in the classroom to create assignments that will make it more difficult for students to use AI tools improperly and some that will aid in helping students to master AI tools when they are appropriate to use for an assignment:

1. Create assessments that cannot be answered by AI such as:
   a. Have students write about personal experiences or discuss their learning experience in the class
   b. Ask students to critique the default answers created by tools such as ChatGPT to questions that were created for the assignment

   c. Require students to cite primary sources to back up their opinion or claims
   d. Require students to write about current events, which are not (at least currently) known to tools such as ChatGPT
2. Require students to produce more than one draft of their original work
3. Ask students to create videos, podcasts, or slideshows with audio recordings
4. Let students know that their work will be checked by an AI detector (Tian, et al. 2024).

6. LIMITATIONS

This research sought to test whether GPTZero could accurately detect human-generated, AI-generated, or mixed-generated writing samples. A limitation to the study is that only GPTZero was used to analyze the samples. Future studies should compare results from GPTZero to other similar products such as ZeroGPT or Detect GPT. It is also important to note that the screenshots used in this article were created in July 2024; at the time this article was written and are subject to change as the platform continues to progress.

7. CONCLUSIONS

This study sought to determine if GPTZero can accurately detect if writing samples were created by a human, AI or a combination of both. Based on the outcomes of this experiment, the researchers determined that GPTZero, at the time of this research, July 2024, can accurately be used to make this determination. It is important to note that this could change at any time dependent on the advancements of AI and how quickly the developers can update GPTZero to keep up with the newest AI developments.

8. REFERENCES

Adeshola, I. (2023). The opportunities and challenges of ChatGPT in education. *Interactive Learning Environments*, 1–14. https://doi.org/10.1080/10494820.2023.2253858

Baidoo-Anu, D., & Ansah, L.O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. Journal of AI, 7(1), 53-62. http://dx.doi.org/10.2139/ssrn.4337484

Casal, J.E., Kessler, M. (2023, December). Can linguists distinguish between ChatGPT/AI and human writing? A study of research ethics and academic publishing. *Research Methods in Applied Linguistics, 2*(3), 100068. https://doi.org/10.1016/j.rmal.2023.100068

D'Agostino, S. (2023, June). Turnitin's AI detector: higher-than-expected false positives. Inside Higher Ed. https://www.insidehighered.com/news/quick-takes/2023/06/01/turnitins-ai-detector-higher-expected-false-positives

Elkhatat, A.M., Elsaid, K., & Almeer, S. (2023). Evaluating the efficacy of AI content detection tools in differentiating between human and AI-generated text. *International Journal for Educational Integrity, 19*(17), 1-16. https://doi.org/10.1007/s40979-023-00140-5

Johnston, H., Wells, R., Shanks, E., Boey, T., & Parsons, B. (2024). Student perspectives on the use of generative artificial intelligence technologies in higher education. *International Journal for Educational Integrity, 20*(2), 1-21. https://doi.org/10.1007/s40979-024-00149-4

Kyaw, A. (2023, December 14). *Report: Almost half of high school students use AI for schoolwork.* Diverse Education. https://www.diverseeducation.com/student-issues/article/15660259/report-almost-half-of-high-school-students-use-ai-for-schoolwork

Liu, Z., Yao, Z., Li, F., Luo, B. (2024, March). On the detectability of ChatGPT content: Benchmarking, methodology, and evaluation through the lens of academic writing. https://doi.org/10.48550/arXiv.2306.05524

Lo, C.K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. *Education Sciences, 13*(4), 410. https://doi.org/10.3390/educsci13040410

Nam, J. (2023, November 22). *56% of college students have used AI on assignments or exams.* Best Colleges. https://www.bestcolleges.com/research/most-college-students-have-used-ai-survey/

Ng, D.T.K., Leung, J.K.L., Chu, S.K.W., & Qiao, M.S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence, 2*(2021), 100041.

https://doi.org/10.1016/j.caeai.2021.100041

OpenAI. (2023, March). GPT-4 technical report. https://cdn.openai.com/papers/gpt-4.pdf

OpenAI. (2024, July). How can educators respond to students presenting AI-generated content as their own? https://help.openai.com/en/articles/8313351-how-can-educators-respond-to-students-presenting-ai-generated-content-as-their-own

Paullet, K, Pinchot, J., Kinney, E., & Stewart, T. (2024). Can GPTZero detect if students are using artificial intelligence to create assignments? IACIS 2024 Conference Proceedings.

Rasul, T., Nair, S., Kalendra, D., Robin, M., de Oliveira Santini, F., Laderia, W.J., Sun, M., Day, I., Rather, R.A., & Heathcote, L. (2023). The role of ChatGPT in higher education: Benefits, challenges, and future research directions. *Journal of Applied Learning & Teaching, 6*(1), 1-16. http://journals.sfu.ca/jalt/index.php/jalt/index

Sadasivan, V.S., Kumar, A., Balasubramanian, S., Wang, W., & Feizi, S. (2024, February). Can AI-generated text be reliably detected? https://arxiv.org/pdf/2303.11156

Shrivastava, R. (2024). With seed funding secured, AI detection tool GPTZero launches new browser plugin. *Forbes.* https://www.forbes.com/sites/rashishrivastava/2023/05/09/with-seed-funding-secured-ai-detection-tool-gptzero-launches-new-browser-plugin/?sh=1ef814b33f7b

Tian, E. (2023). Ways to by-pass AI detection? https://gptzero.me/news/gptzero-by-passers

Tian, E., & Cui, A. (2024). GPTZero: Towards detection of AI-generated text using zero-shot and supervised methods.

Steponenaite, A., & Barakat, B. (2023, July). Plagiarism in AI empowered world. In *International Conference on Human-Computer Interaction*, 434-442. https://sure.sunderland.ac.uk/id/eprint/15622/7/Conference_paper_template_AI_manuscript_edit2.pdf

Tian, E. (2023, March). Ways to by-pass AI detection? GPTZero. https://gptzero.me/news/gptzero-by-passers

Tossell, C.C., Tenhundfeld, N.L., Momen, A., Cooley, K., & de Visser, E.J. (2024). Student perceptions of ChatGPT use in a college essay assignment: Implications for learning, grading, and trust in artificial intelligence. IEEE Transactions on Learning Technologies, 17, 1069-1081. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=10400910

Walters, W.H. (2023). The effectiveness of software designed to detect AI-generated writing: A comparison of 16 AI text detectors. *Open Information Science, 7*(1). https://doi.org/10.1515/opis-2022-0158

Zhang, Y., Ma, Y., Liu, J., Liu, X., Wang, X., & Lu, W. (2024, April). Detection vs. anti-detection: Is text generated by AI detectable? *International Conference on Information*, 209-222. https://doi.org/10.1007/978-3-031-57850-2_16

Teaching Case

Kibbles & Bytes: Developing a Database for an Animal Shelter Silent Auction

Dana Schwieger
dschwieger@semo.edu
Department of Management
Southeast Missouri State University
Cape Girardeau, MO 63701, USA

Hook

Whispering Hills's Animal Shelter recently held a successful, yet problematic, dinner and silent auction to raise funds for operations. Although the fundraiser attracted more attendees and item bidders than they had expected, the volunteer staff was ill-equipped to handle the onslaught of winning bidders at the end of the night. The shelter needs our help to transform their manual silent auction process into a more efficient and streamlined system.

Abstract

Many nonprofit organizations rely upon volunteers and fundraising events to supplement their operating budgets. Unfortunately, these budgets are often so tight that they do not allow for supplemental purchases beyond daily operations. Many nonprofit organizations would love to have volunteer help who could create software to meet their specific needs. However, many do not think to contact local universities for interns or class projects to help them with their needs. Thus, faculty looking for real-world projects to incorporate into their classrooms are often not aware of the needs in their community nor whom to contact. In this teaching case, the students are asked to design and develop a database to support a silent auction fundraising event. System needs and requirements are presented in a conversational format simulating the client requirements interview process. The case can be used in a systems analysis and design, database development or graduate level management information systems course. The case focuses upon the development of a donation management system for a small silent auction with donors, donations, and auction attendees. Multiple assignment options are provided, allowing instructors to select an assignment based upon course material coverage. Suggested assignments include the development of process modeling diagrams such as data flow and swim lane diagrams, database design diagrams such as UML diagrams or ERDs, and database artifacts such as tables, queries, and reports.

Keywords: Teaching Case, Process Design, Swimlane Diagrams, Database Design, Silent Auction

Recommended Citation: Schwieger, D., (2025). Kibbles & Bytes: Developing a Database for an Animal Shelter Silent Auction. *Information Systems Education Journal* v23, n6 pp 53-64. DOI# https://doi.org/10.62273/HGTB4189

Kibbles & Bytes: Developing a Database for an Animal Shelter Silent Auction

Dana Schwieger

1. INTRODUCTION

Nonprofit pet rescue organizations often face a multitude of compounding challenges including staying current with changing accounting and regulatory requirements, high employee and administrative turnover, increasing pet intake numbers, shrinking governmental funding, unsteady income streams, shoestring budgets, and covering administrative costs (Alley Cat Allies, 2024; Matthews & Bloomberg, 2024). In addition, many nonprofits are in communities where high numbers of the population earn below the median U.S. household income level (Alley Cat Allies, 2024). Thus, little, if any, money is available to allocate toward nonessential administrative improvements and special projects. Hope for Paws, for example, (an animal rescue facility in Los Angeles) did not have the team capacity to implement traditional fundraising activities. They turned to social media and other resources to obtain needed financial support (Freewill, 2021).

Technical solutions are a means to fulfill some of the needs and human resource shortfalls that nonprofits face. In this case, administrators at Whispering Hills Animal Shelter turn to the development of a silent auction database management system to streamline their annual fundraiser and silent auction, provide better tracking of donations, donors, and event attendees, and improve the overall accuracy and availability of silent auction data.

2. WHISPERING HILLS ANIMAL SHELTER

“What time did you get home last night?” Mark asked Lisa as she joined him at the kitchen table. Lisa was a member of the Whispering Hills’ Animal Shelter advisory board. She had overseen the silent auction part of the big annual fundraiser they had the night before.

“Late,” She sighed as she took a sip of her coffee. “I think I finally got home about midnight. It took us longer than we expected to collect the money and distribute the auction items. I also stayed and after the auction was over to help clean up.”

“What was the hold-up?’ Mark asked. “You thought you would be home by 10:00 p.m. at the latest when I left last night.”

“We were slammed with everyone wanting to pick-up and pay for their silent auction items at the same time,” Lisa continued. “We also had to smooth some ruffled feathers of some of our attendees. People got tired of having to stand in line and wait to have their bid sheets found and winning bid amounts due totaled, especially those who were at the back of the line. I’ll bet those folks at the back of the line had to wait for over an hour and a half!

“We really need to get the process fixed before next year’s fundraiser. It earns a big chunk of the shelter’s budget. I’m wondering if there is some way we can automate it? I’m supposed to have lunch with my friend, Sandy, today. I’m going to see if she can help.”

3. A WORKING LUNCH

Sandy was an MBA student at the local university. She and Lisa had become friends while working on a database project for a community conference for local teen girls. Sandy had diagrammed the steps in the conference registration process to find bottlenecks in the procedures as well as designed and developed a registration database for the conference. As the waiter walked away from their table with their order, Sandy asked Lisa, “Tell me about last night’s fundraiser. Did it do as well as you had hoped?”

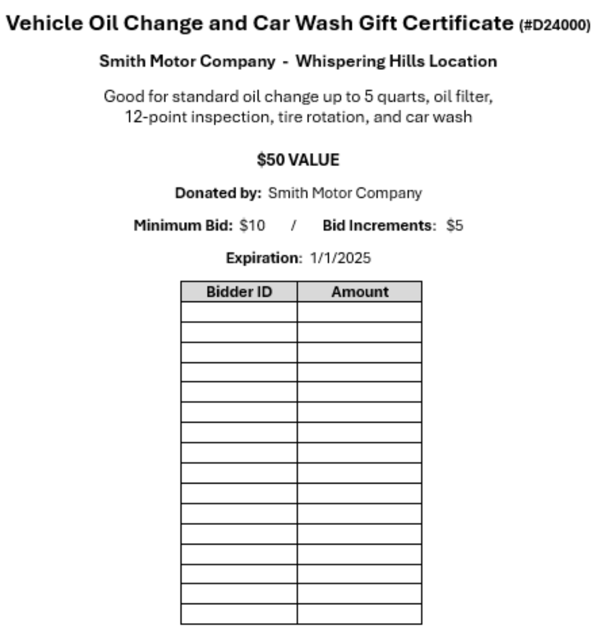
“Overall” Lisa started, “it was one of the most successful fundraising events we have ever had. We had more attendees and auction items than we have had at any of our other events. We also were able to raise more money than we expected. However, we weren’t prepared to handle everyone when they were ready to pay for their items at the silent auction. So, I’m hoping it doesn’t turn people off from coming next year.”

“What was the problem?” Sandy asked. “I’m not really familiar with your event or what a silent auction is, so you’ll have to tell me that as well.”

The Fundraiser
"For the past two years," Lisa stated, "Whispering Hills Animal Shelter has held a dinner and silent auction to raise funds to help with shelter operational expenses. It was new last year, so we did not have many attendees. However, this year we had an entertainer perform. We also made a concerted effort to get the word out which resulted in the sale of about 250 tickets for this year's event. People purchased tickets at the shelter or from one of our community partners, so we didn't collect any information about attendees before the day of the event. Besides the catered meal and entertainment, we also had a silent auction."

Sandy was quiet for a moment. "I'm not sure what that is, can you explain?"

The Silent Auction
"Absolutely," replied Lisa. "A silent auction contains items donated, mostly by businesses, for people to bid on. Some of the items are gift certificates to be used at the different businesses for items such as pizza, hotel rooms, or oil changes. However, there are also some tangible items for auction as well, such as gift baskets, sports memorabilia, or hand-crafted pieces of art that people can see and touch. The gift certificates and items are displayed on the tables with their bid sheets before the event begins."


Vehicle Oil Change and Car Wash Gift Certificate (#D24000)

Smith Motor Company - Whispering Hills Location

Good for standard oil change up to 5 quarts, oil filter, 12-point inspection, tire rotation, and car wash

$50 VALUE

Donated by: Smith Motor Company

Minimum Bid: $10 / **Bid Increments:** $5

Expiration: 1/1/2025

Bidder ID	Amount

Figure 1 – Bid Sheet Example

Bid Sheets
"What do the bid sheets look like," asked Sandy.

"They're pretty simple," said Lisa, handing her a sample (Figure 1). "At the top of each bid sheet is the item's bidding identification number, the name of the item, a brief description of the item (which is especially important for gift baskets), the name of the donor, the estimated value, and the minimum bid price. Beneath that information, and filling the majority of the page, is a grid containing two columns in which bidders write their bidder ID and their bid amount."

Bidding Process
Lisa paused while Sandy studied the sheet. "When someone bids on an item," Lisa continued. "If they are the first bidder, they will write their number on the first line along with the minimum bid amount or a higher amount of their choosing. If someone else wants that item, they will write their bid number on the next empty gridline along with their bid amount which is higher than the previous person's bid amount. This bidding process will continue for each item until the end of the auction which is set when the event is advertised. The auction is called a 'silent' auction because each person writes down their bid amount rather than responding to the calls of an auctioneer."

Bidder Registration
"How do they get their bidder IDs?" Sandy asked as she laid the bid sheet on the table.

"When each auction attendee registers at the registration table," Lisa said, "they are asked if they want a bidder ID and, if so, they fill out a form with their name, address, phone number, email address, contact preference, and an assigned bidder ID.

The bidder ID is the number that they will write down on the grid for an item on which they wish to bid. As attendees register and receive their bidder ID, they can then start looking at the items up for bid and placing their bids."

Bidding
"Do you have to place bids?" Sandy asked.

"No," Lisa responded. "Bidders do not have to bid on anything. However, most bidders will usually bid on multiple items. Bidders often bid multiple times on the same item throughout the night as other bidders outbid them. Once a bidder is outbid, they are no longer obligated to purchase that item and, if they want the item, will have to rebid by writing their bidder ID number beneath the last highest bid as well as their new bid amount higher than the last highest bid amount.

"As the night draws to a close," Lisa continued, "the number of bids being made intensifies. About ten minutes before the auction is set to close, we make a final call for bids before the sheets are collected. At that time, there are usually several people circling the tables ready to write down a new higher bid in case someone tries to outbid them at the last minute.

"Thus," Lisa paused, "last night, most people did not know whether they had won an item until they came up to the registration table at the end of the night to pay for their bid. There were some people who stood in line for over an hour only to find out when they arrived at the table that they had been outbid. Needless to say, those people were rather upset."

"Understandable," Sandy noted as she reflected upon what she had just heard. "How many people were affected and why was it so bad? Why isn't the auction online?"

"Of the 250 people who attended the event last night. I would guess that we had about eight to ten people who stood in line for nothing. We only had two people working at one table to handle everyone trying to leave at one time, so I think that was part of the problem," Lisa replied. "I had thought about moving the auction online, but not everyone feels comfortable with online auctions. Also, if the auction were online, there wouldn't be much for donors to do at our event besides eating and listening to the entertainment. People seem to enjoy the entertainment factor of silent auctions; and, they add an air of excitement to the evening. There is also a little bit of a furor, during the circling phase which spurs last minute bidding to drive up our final donations. So, it would be hard to lose that."

"If you want to keep the paper process, what role do you have in mind for the database?" Sandy asked.

4. THE DATABASE

Pre-Event

"I'm thinking that we could have all of the auction donor and item data entered into a database before the auction starts," Lisa said. "We could also enter all of the attendee registrations into the database as people pre-purchase tickets. An attendance list could be printed before the event to check people off as they arrive and to assign bid numbers. For those people purchasing tickets at the door, we could enter their data directly into the database the night of the event. Data that we would collect would be things like their name, address, phone number, email address, bidder ID, and preferred means of contact for the night of the event."

Night of the Event

"At the end of the evening," Lisa continued, "we can pick up all of the bid sheets, enter the winning bid number and amount for each item into the database, run a report listing all of the winning bid numbers and amounts, and then post that report list as a web page on the shelter's website. People could go to the web page to see what they won as well as the amount owed for each item. It would also be nice if individual reports could be generated for each winning bidder listing the items that they won as well as the total amount they owed and sent out to each winner as an email or text message with information for our online payment system. They could then pay for their items electronically before they get to the check-out table and just show us the receipt on their phone and pick up their items."

Post Event

"Then what happens," Sandy asked.

"Once we have an attendee's information collected," replied Lisa. "We can use that data to send communications to them in the future. We can also just update that information for future auctions so that person will not have to go through the process of filling out a registration form every year. They would, however, have to be assigned a new bidder ID every year."

"You had mentioned collecting donor data too. What do you have in mind?" Sandy asked.

Donor Data

"Besides from the data used to describe each item," Lisa said, "we would also want to collect data about each of the donors for each of the items so that we can send them a thank you note and a receipt detailing their charitable contribution for their tax records.

"The kind of information that we would want to collect about each donor would include the donor's name, contact name, street, city, state, zip code, email address, work phone, and cell phone. We would also assign each donor an ID for our database.

"For each donated item, we will need to know the name of the item, a description of the item, the item's value, an expiration date for the item if applicable (gift certificates usually have an expiration date), and we will assign the item an ID. Donors often provide more than one item, so each individual item would need to have an item ID. We also hope each donor will donate items for future auctions, so we will need to be able to associate each year's auction item to the appropriate donor.

"Of course, protecting the data is paramount. The database would need to contain safeguards to not only keep the data safe, secure, and free of errors, but we would also want to ensure the privacy and protection of donor and attendee data."

5. REPORTS

"I think you have already touched on this a bit, but what kind of reports would you like to be able to run with your database?" Sandy asked.

Event Reports
"Well," Lisa stated, "I have already mentioned a couple of reports that we need for the end of the evening. We would like a list of winners that will be posted as a web page that will include the item IDs, item names, bidder IDs, and the winning bids. We would also like to be able to send an individual message out to each person at the end of the night indicating the item(s) that they won and the total amount they owe. That message would act as a receipt, so it would be nice if we could list the bidder ID, the item IDs, item names, each amount owed, and then total the entire amount owed for that person."

Donor Reports
Sandy thought for a moment. "What about the donors?"

"We will also want to be able to send a report to each donor listing each of the items that they donated including the item ID, item name, item description, item category, value of the item, number of items donated, and total value of items donated. As we prepare for future auctions, it would be nice to be able to run a list of past donations as well as a list of donor names, contact names, addresses, phone numbers, and list of items donated so that when one of our volunteers solicits items for future silent auctions, they will have an idea of who has donated to us in the past and what they provided."

Attendee Reports
"Finally," Lisa said, "it would be nice to have an attendance list for the night of the event so that we can check people off as they arrive. We would also like to be able to send communications to attendees as well. For instance, it would be nice to send an email reminder out to ticket holders to remind them about the event and start generating enthusiasm for the auction. It would also be nice to send an email out to all attendees after the event thanking them for their support of the event and notifying them of upcoming shelter events. Thus, we will want to be able to send personalized emails that will include the person's name."

Wrapping Up
"You've put a lot of thought into this." Sandy noted as the waiter brought their lunch order to their table. "Let me start working on this for you to see if we can come up with a solution. I want to start by drawing out the processes to make sure I understand what is being done, the data that needs to be collected, and the reports that need to be generated. This will help me to see if I am missing anything. I'll try to send you some diagrams and report mock-ups by the end of the week."

6. ASSIGNMENTS

This project could take multiple paths depending on the role and activities your instructor has in mind for you. Clarify with your instructor the role that you will play.

Process Model Diagrams
Assume the role of Sandy, the MBA-student. Draw out the functional process steps to verify that you have identified all of the steps and understand how the process works.

1. Create diagrams modeling each of the processes.
2. Write short narratives to accompany your diagrams to verify and support your interpretation of the process.
3. Once the narratives are written:
    a. Compare the narratives to the diagrams to identify and/or clarify missing steps in the process.
    b. Compare the narratives to the actual description in the case to identify missing steps in the diagram or areas needing clarification.
4. As the diagrams are developed, record any assumptions or interpretations you make, regarding the processes, in a separate document.

Data Flow Diagrams
Assume the role of Sandy, the MBA-student. Create a data flow diagram to illustrate the flow of data through the silent auction management process to verify that you understand how the data is collected, processed, stored, and disseminated.

1. Create a diagram modeling the flow of data through the process.
2. Write a short narrative to accompany your diagram to verify and support your interpretation of the process.
3. Once the narrative is written:
   a. Compare the narrative to the diagram to identify and/or clarify missing steps in the process.
   b. Compare the narrative to the actual description in the case to identify missing steps in the diagram or areas needing clarification.
4. As the diagrams are developed, record any assumptions you make, regarding the processes, in a separate document.

Research Commercially Available Software Packages
Assume the role of Sandy and research commercially available donor management and silent auction systems. Keeping the characteristics of the shelter in mind, write a memo to Lisa describing the two best products available. In your memo, provide:

- the name of the software;
- the URL to the software's website;
- the cost;
- how the software is accessed (cloud-based or installed locally);
- a brief description of the software and its capabilities;
- pros and cons of the software; and
- your recommendation, buy or build and if buy which one.

Systems Analysis Design and Database Development
Assume the role of Sandy, the MBA-student. You want to build the database. You want to:

1. Accumulate the functional and technical requirements for the system.
2. Prioritize the requirements.
3. Create system development diagrams.
4. Create a data dictionary.
5. Create the database.
6. Create queries to generate records needed for event attendance; lists of donors, donated items, and winning bids; and data needed for various mail-merged emails (e.g., item donors, bid winners, thank you letters. and general communication).
7. Create reports for the queries including event attendance, donor, donated items, and winning bids lists, and informational emails and letters to donors, attendees, and winning bidders.
8. Incorporate privacy, security, and data error handling measures throughout the database. Include a brief written report describing:
   a. the measures that were taken,
   b. the data those measures will protect, and
   c. how those measures will protect the data.
9. As the database is developed, record any assumptions made in a short report.

Future System Enhancements
Once the initial system has been developed, future updates can be made to further enhance its capabilities such as:

1. Automation of reports and messages,
2. Real-time updates of bidding progress,
3. Enhanced privacy and security measures,
4. Integration with other systems,
5. Scalability, and
6. Data analytics.

Students may want to:

1. Write a short narrative explaining how one or more of the capabilities could be incorporated into their system and the value they would provide to the organization.
2. Incorporate one or more of the capabilities into your system.

7. POTENTIAL CHALLENGES & OBSTACLES

System Complexity
From a macro level perspective, the silent auction system may initially seem quite complex. However, focusing on the individual separate subprocesses such as registering donors, recording donated items, registering attendees, entering winning bids, etc. will help to simplify the complexities of the system.

Time Management
Projects normally take longer than one would expect. Breaking the project down into small goals to be completed over a period of time will allow time for asking the instructor questions that may arise.

Diagrams and Symbols
Should a student be unfamiliar with business process mapping or data flow diagrams, there are many resources available online that describe the

diagrams and provide examples of the diagrams and their symbols including:

- Creately Business Process Modeling Techniques with Examples: https://creately.com/blog/bpm/business-process-modeling-techniques/
- Asana’s Guide to Process Mapping Process Mapping https://asana.com/resources/process-mapping
- The tutorials associated with business modeling software such as Lucidchart, draw.io, smartdraw.com, and Viso.

8. CONCLUSION

Sandy worked all week formalizing her ideas. When she and Lisa met to discuss her database vision, diagrams, and mock-ups, Lisa was pleased with her work and encouraged her to start working on the project as soon as possible.

Examples of some of the report mock-ups can be found in the appendix.

9. REFERENCES

Alley Cat Allies. (n.d.). *Case study: Homeward bound pet adoption center. Alley Cat Allies.* Retrieved from https://www.alleycat.org/resources/case-study-homeward-bound-pet-adoption-center/

FreeWill (2021, November 2). *How Hope for Paws raises crucial funds & helps donors make plans for their pets*. Retrieved from https://www.nonprofits.freewill.com/resources/case-studies/hope-for-paws

Matthews, S. & Li, D. . (2024). *Surge in unwanted dogs fuels ‘crisis’ across U.S. animal shelters.* Time. Retrieved from https://time.com/6552905/stray-dogs-animal-shelters-overcrowding/

APPENDIX A

List of Winners Report

Whispering Hills Shelter Silent Auction

Thank you so very much for your attendance and participation in the annual Whispering Hills' Animal Shelter silent auction. Below is the list of winners and their winning bids for each item.

	Item ID	Item Name	Bidder ID	Winning Bid Amount.
1	D24000	SMC – Gift Cert. $100	112	$90
2	D24001	SMC – Gift Cert. $ 50	206	$45
3	D24002	SMC – Gift Cert. $250	176	$245
4	D24004	Schwinn Bicycle	54	$345
5	D24009	Movie Theater Tkts - 4	96	$30
...				
...				
199	D24250	WalMart – Gift Card $25	112	$25
200	D24251	KFC – Gift Card $25	229	$25

APPENDIX B

Winning Bidder Email Receipt Report Example

Whispering Hills Shelter Silent Auction

Bid ID: 112
Amanda Gomez
219 Rosewater Lane
Whispering Hills, MO 63901

Thank you so very much for your attendance and participation in the annual Whispering Hills' Animal Shelter silent auction. The Shelter would not be able to continue without supporters like you. We are so grateful for you and your generosity. Listed below are the items that you won. Please pay electronically at your seat before the evening ends or write a check to the Shelter to have ready at checkout. Winning items will be available at checkout by last name.

	Bidder ID	Item ID	Item Name	Winning Bid Amount.
1	112	D24000	SMC – Gift Cert. $100	$90
2	112	D24015	CFA – Gift Cert. $25	$25
3	112	D24016	Culver's – Gift Card $25	$25
				$140

For questions, please contact the office at (555) 555-2222.

Sincerely,

Lisa

Whispering Hills' Animal Shelter

Tel (XXX) 555-2222 100 Shelter Lane
Fax Fax (XXX) 555-2223 Whispering Hills, MO 63901

APPENDIX C

Letter to Donors Report Example

Whispering Hills Shelter Silent Auction

Amber Smith
Smith Motor Company
115 Automotive Lane
Whispering Hills, MO 63901

Thank you so very much for your donation to the annual Whispering Hills' Animal Shelter silent auction. This fund raiser is critical to funding our yearly operations and covers almost 20% or our annual budget. The Shelter would not be able to continue without supporters like you. We are so grateful for you and your generosity. Listed below are the items that we have listed as your donation. If you see a mistake, please let us know. If the item still needs to be delivered to the shelter office, please let us know and we will be glad to make arrangements with you at your convenience.

ItemID	Item Name	Item Description	Category	Value	# of Items Donated	Total Value
D24000	SMC – Gift Cert. $100	Gift Certificate for Vehicle Detailing	Gift Certificate	$100	2	200
D24001	SMC – Gift Cert. $50	Gift Certificate for Oil Change and Car Wash	Gift Certificate	$50	4	200
D24002	SMC – Gift Cert. $250	Gift Certificate toward new tires or vehicle Maintenance	Gift Certificate	$250	1	250
				Total	**5**	**$650**

For questions, please contact the office at (555) 555-2222.

Sincerely,

Lisa

APPENDIX D

List of Donations Report Example

Silent Auction – 2024 Donations

ItemID	Item Name	Item Description	Category	Value	# of Items Donated	Total Value
Smith Motor Company, 115 Automotive Lane, Whispering Hills, MO 63901 Contact: Amber Smith (555) 555-3331. Email: asmith@smithmotor.com						
D24100	SMC – Gift Cert. $100	Gift Certificate for Vehicle Detailing	Gift Certificate	$100	2	200
D24101	SMC – Gift Cert. $50	Gift Certificate for Oil Change and Car Wash	Gift Certificate	$50	4	200
D24102	SMC – Gift Cert. $250	Gift Certificate toward new tires or vehicle Maintenance	Gift Certificate	$250	1	250
Chick-Fil-A, 225 Restaurant Lane, Whispering Hills, MO 63901 Contact: Jason Stevens (555) 555-3332. Email: jstevens@whmcfa.com						
D24249	CFA- Birthday Party	Gift cert. for Bday Party for 10 kiddos ($150)	Gift Certificate	$150	1	$150
D24250	CFA- Gift Card $25	Gift card for CFA - $25	Gift Card	$25	4	$100
Mike's Bikes, 165 Sports Road, Whispering Hills, MO 63901 Contact: Mike Waters (555) 555-3333 Email: mike@mikesbikes.com						
D24104	Schwinn Bike	Red children's bike	Sports Item	$350	1	$350

APPENDIX D

Donor Information Lists

Silent Auction Item Donor Information List

	Donor ID #	Name	Phone	Email	Address	Communication Preference
1	D001	Alex Turner	(555) 123-4567	alex.turner@email.com	123 Cardinal Ave, MO	Text
2	D002	Samantha Wells	(555) 123-4568	s.wells@email.com	456 Vine St, MO	Text
3	D003	Michael Roberts	(555) 123-4569	m.roberts@email.com	789 Artisan Way, MO	Phone
4	D004	Jessica Franklin	(555) 123-4570	j.franklin@email.com	101 Dells Rd, MO	Text
5	D005	Daniel Gonzalez	(555) 123-4571	d.gonzalez@email.com	202 Gourmet Blvd, MO	Text
6	D006	Olivia Peterson	(555) 123-4572	o.peterson@email.com	303 Music Hall Rd, MO	Text
7	D007	Ethan Clark	(555) 123-4573	e.clark@email.com	404 Chef St, MO	Text
8	D008	Ava Johnson	(555) 123-4574	a.johnson@email.com	505 Serenity Ln, MO	Text
9	D009	Lucas Martinez	(555) 123-4575	l.martinez@email.com	606 Tech Dr, MO	Text
10	D010	Emma Thompson	(555) 123-4576	e.thompson@email.com	707 Canvas Rd, MO	Phone

Silent Auction Attendance List

	Attendee ID #	Name	Street	Zip Code	Email	Phone
1	A24001	John Doe	123 Maple Drive	54321	johndoe@email.com	(555) 456-7890
2	A24002	Jane Smith	456 Oak Lane	54322	janesmith@email.com	(555) 456-7891
3	A24003	Emily Johnson	789 Pine Street	54323	emilyjohnson@email.com	(555) 456-7892
4	A24004	Michael Brown	101 Birch Road	54324	michaelbrown@email.com	(555) 456-7893
5	A24005	Jessica Davis	202 Cedar Blvd	54325	jessicadavis@email.com	(555) 456-7894
6	A24006	William Martinez	303 Redwood Ave	54326	williammartinez@email.com	(555) 456-7895
7	A24007	Sarah Wilson	404 Spruce Way	54327	sarahwilson@email.com	(555) 456-7896
8	A24008	David Anderson	505 Elm Street	54328	davidanderson@email.com	(555) 456-7897
9	A24009	Amanda Thomas	606 Walnut Road	54329	amandathomas@email.com	(555) 456-7898
10	A24010	James Jackson	707 Chestnut Drive	54320	jamesjackson@email.com	(555) 456-7899