eLmL 2026

The Eighteenth International Conference on Mobile, Hybrid, and On-line Learning

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eLmL 2026 Editors

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eLmL 2026

Forward

The Eighteenth International Conference on Mobile, Hybrid, and On-line Learning (eLmL 2026), held between May 24, 2026, and May 28, 2026, in Venice, Italy, continued a series of events bringing together federated views on mobile learning, hybrid learning, and on-line learning.

eLearning refers to on-line learning delivered over the World Wide Web via the public Internet or the private, corporate intranet. The goal of the eLmL 2025 conference was to provide an overview of technologies, approaches, and trends that are happening right now. The constraints of e-learning are diminishing, and options are broadening as the Web becomes increasingly easy to use and the technology becomes better and less expensive.

The event provided a forum where researchers were able to present recent research results and new research problems and directions related to them. The topics covered aspects related to tools and platforms, on-line learning, mobile learning, and hybrid learning.

We take here the opportunity to warmly thank all the members of the eLmL 2026 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank the authors who dedicated time and effort to contribute to eLmL 2026. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the eLmL 2026 organizing committee for their help in handling the logistics of this event.

We hope that eLmL 2026 was a successful international forum for the exchange of ideas and results between academia and industry for the promotion of progress in the field mobile and on-line learning.

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Measuring Change – Evaluating Cybersecurity Awareness Before and After a Video-Based Learning Module

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***Abstract*—Cybersecurity awareness among students in non-technical degree programs is often insufficient, despite their extensive use of digital services in everyday life. This study addresses the challenge of improving cybersecurity awareness and self-reported behavior in higher education through low threshold digital learning interventions. The objective is to evaluate whether a video-based learning module can measurably influence students' awareness, attitudes, and behaviors related to cybersecurity. A pre/post study design was applied using two nearly identical standardized questionnaires administered before and after the intervention to answer the research questions. The study involved 104 first-semester undergraduate students who participated in a learning unit consisting of four instructional videos covering core cybersecurity topics. The results indicate that approximately 77% of participants had no prior cybersecurity training, confirming a low baseline level. Descriptive analyses show small but consistent improvements in cybersecurity awareness and selected behavioral indicators, particularly in phishing recognition and online shopping security. However, statistical testing revealed no significant overall differences between pre/post-test results. In conclusion, the findings suggest that video-based learning is effective as an introductory and sensitizing approach for cybersecurity education, but insufficient on its own to produce immediate, significant behavioral change. Future educational designs should therefore combine video-based content with interactive, practice-oriented, and longitudinal learning elements to foster sustained cybersecurity behavior in higher education.**

Keywords-Cybersecurity awareness; video-based learning; higher education; phishing; online shopping security; mobile security; digital behavior change.

I. INTRODUCTION

This section introduces the motivation, research objectives, and overall contribution of the study. It outlines the problem context, formulates the research questions, and positions the work within the broader field of cybersecurity education.

A. Motivation and Background

In an increasingly digitalized world, cybersecurity has become a critical concern. For young adults who interact daily with digital devices and online services, a fundamental understanding of security measures is essential. Higher education institutions face the challenge of not only delivering subject-specific knowledge but also fostering security awareness among their students. At OTH Regensburg, the degree programs Digital Business Management and International Business Management include the course ”Digital Technology Skills” in the first semester. As part of this learning unit, a dedicated activity called the Cybersecurity Challenge is conducted to strengthen students practical understanding of cybersecurity.

B. Research Objectives and Questions

The course Digital Technology Skills combine in-class sessions with an online learning platform where students engage with instructional videos outside the lecture. As part of the Cybersecurity Challenge, students were required to watch four videos addressing key topics in cybersecurity, including password security, phishing awareness, online shopping, safe browsing practices, and data protection.

The primary objective of this paper is to examine the impact of this digital learning intervention on students attitudes and behaviors regarding cybersecurity. Specifically, the study aims to:

1) Assess students existing knowledge and practices related to cybersecurity prior to the learning unit.
2) Identify changes in awareness, attitudes, and self-reported behaviors after completing the video-based learning activities.

To achieve these objectives, two standardized questionnaires were administered:

- Part I (Pre-test): Captured baseline knowledge and behavior before the learning unit.
- Part II (Post-test): Conducted after students watched the videos to identify potential changes.

The findings presented in this paper seek to answer the following research questions:

RQ1: What was the initial level of cybersecurity awareness among students?
RQ2: To what extent did the digital learning intervention influence their attitudes and behaviors?

C. Contribution and Structure

The findings of this study aim to provide insights into the effectiveness of digital learning formats in promoting cybersecurity awareness and encouraging tangible behavioral changes among students. By analyzing pre/post intervention data, this paper contributes to the ongoing discussion on how learning approaches can support higher education institutions in addressing cybersecurity challenges.

The remainder of the paper is structured as follows. Section II reviews related work on cybersecurity awareness and digital learning interventions. Section III outlines the conceptual foundation of the video-based learning module. Section IV describes the pre/post study design and data analysis. Section V presents the empirical findings and discusses implications for cybersecurity education. Section VI concludes with a summary and outlook for future work.

II. Related Work

This section reviews relevant literature on cybersecurity awareness in higher education, the effects of digital learning interventions, and the role of video-based and blended learning approaches. It establishes the theoretical and empirical foundation for the present study.

A. Baseline Cybersecurity Awareness in Higher Education

Prior research consistently shows that higher education students enter university with insufficient cybersecurity awareness, particularly regarding phishing, password security, and digital privacy [1]. Large-scale surveys reveal that approximately 30–40% of students cannot correctly identify phishing attempts [2] [3]. Simulated attack studies show high susceptibility, with 67.67% of participants disclosing sensitive information during a WhatsApp-based social engineering simulation [4]; similar behavioral susceptibility has also been observed in academic-community phishing studies [5]. Similarly, assessments using established metrics, such as the Digital Competence Framework for Educators (DigCompEdu) framework, find that 93.5% of students demonstrate only intermediate digital security competence, and just 0.6% reach high competence levels [6].

Baseline misconceptions appear across multiple domains. Students routinely overestimate their ability to identify cyber threats [2] [7], yet fail to label risky scenarios as dangerous [8]. Only certain subpopulations, such as IT majors, show comparatively higher initial preparedness, though even these groups often lack secure habitual behaviors [9]. Collectively, these findings indicate that most university students begin with moderate theoretical knowledge but weak practical behavioral competence, highlighting the need for pedagogically structured interventions that target both cognition and behavior [10].

B. Effects of Digital Learning Interventions on Cybersecurity Attitudes and Behaviors

1) Knowledge Gains: Across studies, digital learning interventions consistently produce substantial improvements in cybersecurity knowledge. Effect sizes ranging from Cohen's $d = 0.81$ to $d = 1.50$ are common in gamified, video-based, and modular e-learning approaches [11] [12]. Even short interventions, such as a 20-minute educational game, yield 50–67% increases in phishing-related knowledge [13].

Gamification is among the most frequently used strategies and has been shown to significantly improve knowledge in areas, such as password management, internet use, and information handling [14]. However, these gains do not always generalize to behavioral intentions or compliance attitudes, indicating a gap between knowing and doing.

2) Behavioral and Attitudinal Change: While knowledge gains are robust, behavioral change is more challenging to achieve. Interventions that rely solely on information dissemination, such as quizzes or passive video consumption, tend to improve cognitive awareness but have limited impact on real-world behavior.

The most successful interventions incorporate:

- repeated practice,
- self-efficacy development,
- simulated or authentic threat exposure,
- reflection or debriefing cycles.

For example, competence-based training using progressive exposure to phishing simulations reduced student vulnerability from 67.67% to 1.67%, ultimately reaching 0% after repeated rounds [4]. Protection Motivation Theory (PMT) grounded studies similarly show that self-efficacy strongly predicts behavioral intention, suggesting that interventions should deliberately cultivate confidence in performing secure behaviors [15].

Overall, the literature indicates that, while digital learning reliably improves cybersecurity knowledge, behavioral and attitudinal change requires specific pedagogical design rather than content delivery alone.

C. Effectiveness of Video-Based Learning Approaches

Blended learning, which integrates digital content with instructor-led components, has emerged as a highly effective approach, particularly for non-technical student populations. Studies employing blended designs consistently show:

- larger effect sizes than stand-alone digital modules,
- better translation of knowledge to applied behavior,
- improved student motivation and engagement.

For example, blended programs incorporating gamification, classroom discussion, and hands-on application demonstrate statistically significant, domain-wide improvements in cyber hygiene behaviors [16]. Even low cost or freemium platforms, such as Kahoot! modules, show strong results when embedded in instructor supported environments [17].

At the same time, research highlights an important caveat: single-session interventions produce short-term gains but are susceptible to decay unless reinforced through spaced repetition [12]. This has direct implications for video-based learning modules, which are often used in short, stand-alone formats. Evidence suggests that such modules are most effective when combined with additional learning activities, such as quizzes, guided practice, or reflection tasks, to strengthen retention and promote behavioral transfer.

D. Synthesis and Implications for the Present Study

The reviewed literature converges on three key insights that directly align with the research questions of this study:

1) *Initial awareness levels.* Initial cybersecurity awareness among higher education students is generally low to moderate, with substantial vulnerabilities in phishing recognition, password hygiene, and digital citizenship. Even when students demonstrate theoretical knowledge, their behavioral susceptibility remains high [2] [4] [6].
2) *Impact of digital interventions.* Digital learning interventions reliably improve cybersecurity knowledge, often with large effect sizes. However, the translation of knowledge into attitudes and secure behaviors depends on factors, such as self-efficacy, practice opportunities, and reinforcement mechanisms. Short video-based modules excel in knowledge transmission but may require supplementary elements to influence behavior [11] [14] [15].
3) *Role of blended learning.* Blended learning provides the strongest overall impact on cybersecurity competence, particularly for non-technical learners. Existing research indicates that blended formats enhance engagement, deepen understanding, and improve both cognitive and behavioral outcomes compared to digital-only approaches [12] [16] [17].

The present study contributes to this body of work by empirically evaluating the impact of a video-based learning module, examining not only knowledge gains but also attitudinal and behavioral indicators. In doing so, it extends prior findings by assessing whether a structured, video-centered intervention can meaningfully shift cybersecurity competence in higher education settings and provide evidence on how video-based learning may support lasting behavior change.

III. Intervention Design and Learning Content

This section presents the conceptual foundation of the video-based learning module examined in this study. The selected videos introduce fundamental cybersecurity concepts, highlight prevalent and emerging threats, and frame cybersecurity as a shared socio-technical responsibility rather than a purely technical concern. Collectively, the videos address cognitive, behavioral, and attitudinal dimensions of cybersecurity competence, which are particularly relevant for students in non-technical degree programs.

A. Video 1: Cybersecurity Fundamentals, Threat Landscape, and Shared Responsibility

The first video introduces cybersecurity as a broad socio-technical discipline concerned with protecting digital assets according to the core objectives of Confidentiality, Integrity, and Availability (CIA) triad, cf. [18]. This framework provides a foundational model for understanding cyber risks and appropriate protection measures across devices, applications, networks, cloud infrastructures, and emerging technologies, such as Internet of Things (IoT) systems. By highlighting the ubiquity of digital technology in everyday life, the video frames cybersecurity as a shared responsibility relevant to both private and professional contexts.

Cybersecurity is further conceptualized as a layered process comprising preventive, detective, and corrective controls, reflecting defense-in-depth principles. The video emphasizes the importance of understanding attacker behavior, attack vectors, and evolving threat methodologies to design effective defenses. Acknowledging that absolute security is unattainable, it introduces incident response and digital forensics as essential components for resilience. Emerging technologies, such as artificial intelligence, are discussed as dual-use factors that support both attacks and defenses. The video concludes by linking theoretical principles to basic cyber hygiene practices, reinforcing the role of informed user behavior in effective cybersecurity.

B. Video 2: Phishing Awareness and Safeguarding Information in Digital Interactions

The second video focuses on cybersecurity risks in online shopping, a common digital activity frequently associated with phishing, fraud, and data breaches, cf. [19]. It emphasizes the identification of trustworthy online shops through careful Uniform Resource Locator (URL) inspection, avoidance of suspicious links, and independent background research. These practices directly address common redirection and fake-shop attack scenarios.

The video introduces transport-layer security as a baseline requirement for protecting sensitive transaction data, highlighting Hypertext Transfer Protocol Secure (HTTPS) and encryption indicators as practical heuristics for non-technical users. It further distinguishes between data protection in transit and data protection at rest, emphasizing that secure storage practices can limit the impact of breaches. Convenience features, such as saving payment information, are framed as usability-security trade-offs, encouraging informed decision-making based on provider reputation, security maturity, and visible certifications. By briefly addressing provider-side responsibilities, the video reinforces the socio-technical nature of secure online transactions.

C. Video 3: Secure Online Shopping and Risk-Aware Transaction Behavior

The third video reiterates the core cybersecurity principles related to online shopping and serves as a reinforcement unit within the learning sequence, cf. [20]. From a pedagogical perspective, repetition supports retention and habit formation, which are critical for cybersecurity behaviors that rely on routine decision-making under time pressure.

Key practices, such as verifying website legitimacy, recognizing phishing indicators, and assessing encrypted communication, are restated to emphasize their role as default behaviors rather than exceptional precautions. The video again highlights the distinction between data protection in transit and at rest, and reiterates the shared responsibility between users and service providers. This reinforcement strengthens the likelihood that learners internalize secure behaviors and

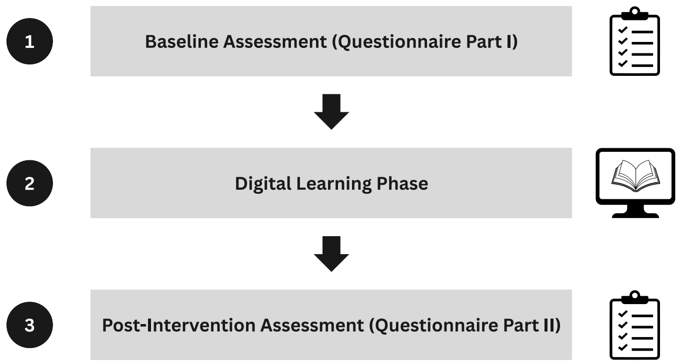

Figure 1. Process of the Cybersecurity Learning Unit.

apply them consistently, supporting the interpretation of post-intervention changes as emerging behavioral consolidation, rather than short-term effects.

D. Video 4: Smartphone Security and Privacy Protection in Mobile Environments

The fourth video addresses cybersecurity risks associated with smartphones, emphasizing that mobile devices are fully fledged computing platforms with comparable threat exposure to traditional computers, cf. [21]. It highlights the importance of regular operating system and application updates, as well as device lifecycle management, to mitigate known vulnerabilities.

Authentication mechanisms, such as PINs and biometric controls, are discussed as effective but limited safeguards that reduce, rather than eliminate, risk. The video examines mobile banking and multi-factor authentication, emphasizing the potential risk of combining authentication and service access on a single device and introducing the concept of factor separation. Platform-specific security assumptions are challenged by highlighting comparable vulnerabilities across mobile operating systems. Additional risks related to malicious applications, phishing, and public wireless networks are discussed, with Virtual Private Network (VPN) usage and situational awareness presented as mitigating strategies. Overall, the video frames mobile security as a combination of technical safeguards and risk-aware user behavior.

IV. METHODOLOGY

The learning unit on cybersecurity consisted of three sequential steps, as illustrated in Figure 1. Baseline Assessment (Questionnaire Part I): Students completed an initial questionnaire comprising 27 questions based on [22] and designed to capture their existing knowledge and behaviors related to cybersecurity. The questionnaire included items assessing both knowledge and self-reported behavior. Example questions include:

- “Do you set a password for your phone?”
- “Do you set a password for your computer?”
- “Do you use a complex password?”

These items were measured using ordinal response scales to capture behavioral tendencies and awareness levels.

Digital Learning Phase: Participants then engaged with four instructional videos on cybersecurity topics. Post-Intervention Assessment (Questionnaire Part II): After viewing the videos, students completed a second questionnaire, which was nearly identical to the first. This follow-up survey included additional questions regarding their subjective perception of the learning content and any intended behavioral changes. Students generated a personal code word to link their responses across both questionnaires to ensure anonymity while enabling data pairing. Participation was voluntary and conducted under strict confidentiality. In addition, both questionnaires were completed online.

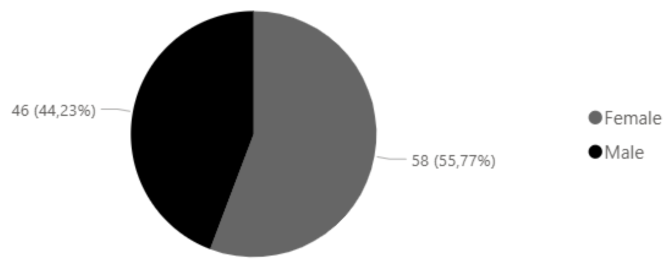

Figure 2. Distribution of Participants by Gender.

Critical Reflection: Several limitations should be considered when interpreting the results. First, the study relies on self-reported data, which may be subject to bias. Second, the short duration of the intervention limits the ability to observe long-term behavioral change. Third, the sample consists of first-semester students, which may restrict generalizability. Finally, the absence of a control group prevents causal attribution of observed changes solely to the intervention.

V. RESULTS AND DISCUSSION

This section presents and interprets the empirical findings of the pre/post-intervention survey, focusing on changes in cybersecurity awareness, attitudes, and self-reported behaviors following the video-based learning module.

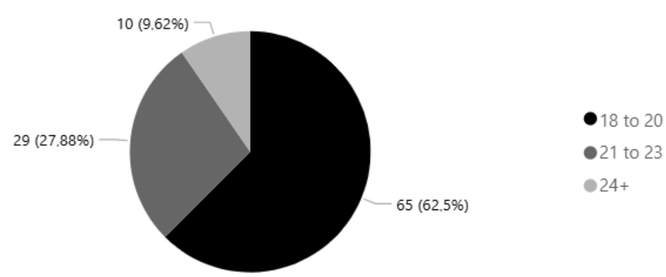

Figure 3. Age Group Distribution of Participants.

A. Sample Characteristics and Baseline Context

The study sample consisted of 104 first-semester students enrolled in business-oriented degree programs. As shown in Figure 2, the gender distribution was balanced, with 58 female (55.77%) and 46 male (44.23%) participants. Figure 3 indicates that most respondents were between 18 and 23 years of age, representing a cohort that is highly active in digital environments.

Baseline exposure to cybersecurity education was limited. As illustrated in Figure 4, 77.88% of participants reported no prior participation in cybersecurity workshops, confirming that the sample largely represents a novice population. This supports the relevance of the intervention and aligns with prior research indicating low to moderate baseline cybersecurity awareness among non-technical students.

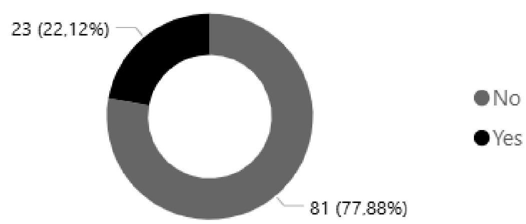

Figure 4. Self-Reported Prior Knowledge.

B. Changes in Awareness and Self-Reported Behavior

Figures 5 to 7 visualize pre/post-test responses for selected cybersecurity domains, including general awareness, password practices, and phishing recognition. Across most items, descriptive analysis shows small but consistent shifts toward more security-conscious responses following the learning module.

Password-related behavior, shown in Figure 5, reveals modest improvements. After the intervention, fewer students reported frequent re-use of the same password across multiple accounts, and a slight increase was observed in responses indicating safer password practices. While these changes are limited in magnitude, they point toward an emerging reflection on personal security habits.

The greatest observable improvement appears in phishing awareness. Figure 6 shows an increase in the number of students who reported knowing what phishing is, alongside a reduction in those who indicated uncertainty. This aligns with the targeted content of the videos on phishing, online shopping, and mobile security, and reflects findings from prior studies that phishing awareness is particularly responsive to short, focused educational interventions.

Figure 7 (Awareness) indicates an increase in self-reported cybersecurity awareness after the intervention, suggesting that the videos successfully heightened students perception of cybersecurity relevance. This effect is particularly important, as awareness is a prerequisite for subsequent behavioral change.

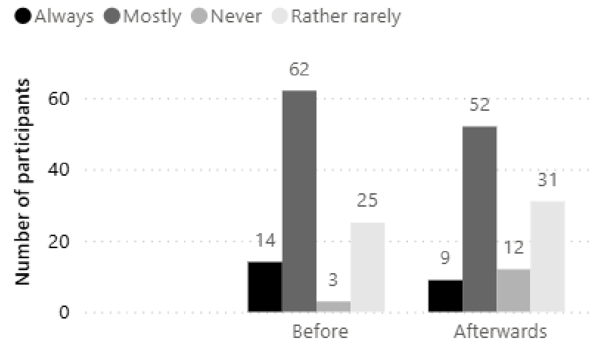

Figure 5. Password Change Awareness.

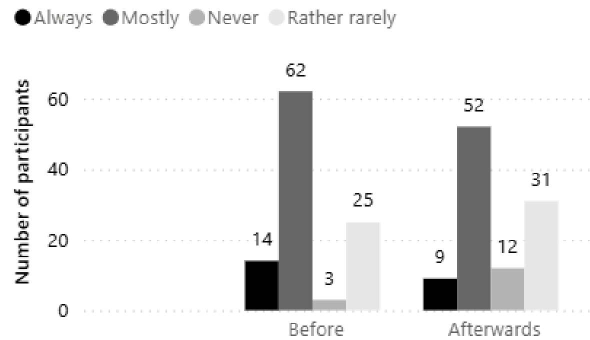

Figure 6. Phishing Awareness.

C. Statistical Analysis

Descriptive statistics show that mean values across questionnaire items ranged from 1.02 to 3.63 in the pre-test and from 1.00 to 3.77 in the post-test, with moderate standard deviations indicating heterogeneous baseline behaviors among students. Quartile distributions suggest that the majority of responses were already clustered in the moderately security-aware range before the intervention.

Correlation analysis yielded a very strong positive Pearson correlation between pre/post-test responses (r = 0.927), indicating high internal consistency and stability in students self-reported behavior patterns across both measurement points. This suggests that the intervention did not fundamentally alter underlying response structures but rather produced incremental shifts within an otherwise stable behavioral framework.

A paired-samples t-test comparing pre- and post-test mean values resulted in $t = 0.543$, $p = 0.616$, indicating no statistically significant difference at the conventional $\alpha = 0.05$ level. The corresponding effect size (Cohen's d) was small, suggesting that the intervention produced only minor changes at the aggregate level. Although statistical significance was not achieved, consistent directional trends across multiple indicators suggest a systematic, small intervention effect. Such patterns may indicate early-stage behavioral change processes that require reinforcement.

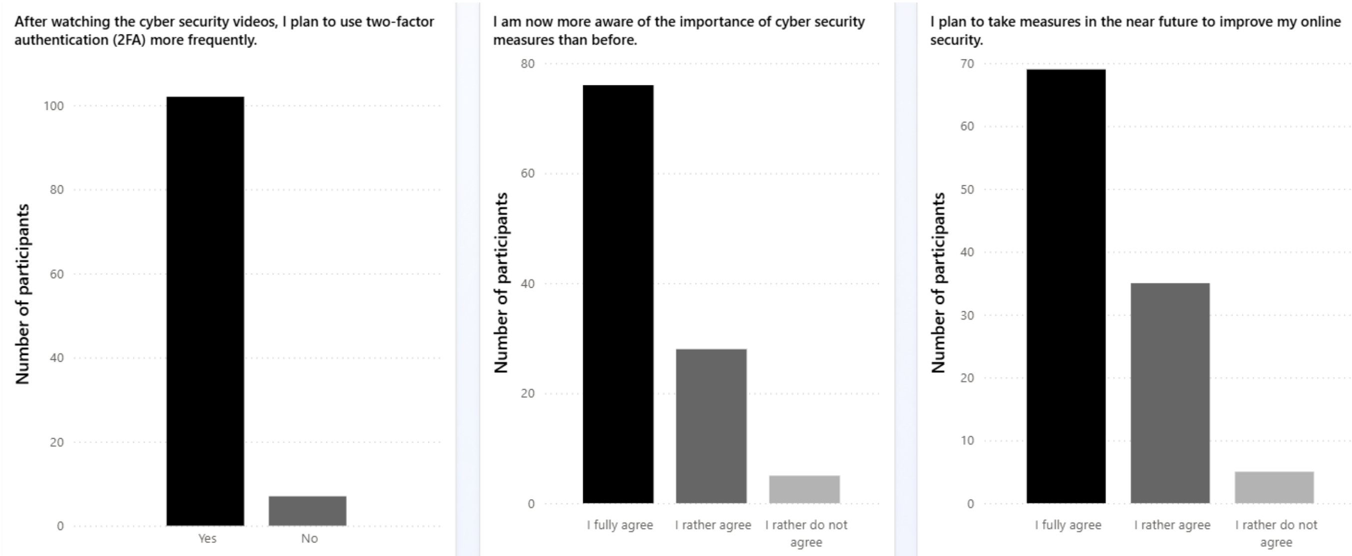

Figure 7. Self-Reported Post-test Participant Awareness.

D. Interpretation and Discussion

The absence of statistically significant differences does not imply that the intervention was ineffective. Instead, the results indicate that the video-based learning module primarily contributed to awareness raising and reflective adjustment, rather than immediate, large-scale behavioral transformation, cf. Figure 7. This interpretation is supported by the visual trends in Figures 5 to 7, which consistently show directional improvements despite limited effect sizes.

Generalizability and Theoretical Implications: Beyond cybersecurity education, the observed distinction between awareness gains and limited behavioral change reflects a broader phenomenon in digital learning and behavioral science. Informational interventions are often effective at increasing cognitive awareness. They are insufficient to trigger immediate behavioral change without reinforcement mechanisms. This aligns with established behavior change theories, such as Protection Motivation Theory, which emphasize the role of self-efficacy, repeated exposure, and contextual relevance. The concept of *reflective adjustment*, observed in this study, therefore represents an intermediate outcome between knowledge acquisition and sustained behavioral change. This intermediate stage may be critical for designing scalable educational interventions across domains, such as data privacy, digital health literacy, or sustainability education.

Several factors may explain these findings. First, the intervention was short and primarily informational, which prior research has shown to be more effective at improving knowledge and awareness than at producing immediate behavioral change. Second, cybersecurity behaviors, such as password management or cautious online decision-making, are habitual and context-dependent, often requiring repeated practice and reinforcement to change sustainably. Third, the strong correlation between pre-/post-test responses suggests that deeply ingrained habits are resistant to change through a single exposure.

Importantly, the results align with existing literature on video-based cybersecurity education, which consistently reports modest short-term behavioral effects but meaningful gains in awareness and risk perception. In this context, the observed improvements in phishing recognition and self-reported awareness represent valuable outcomes, particularly for first-semester, non-technical students.

Overall, the findings suggest that video-based learning modules are well-suited as introductory and sensitizing tools within a broader learning strategy. While they may not be sufficient on their own to produce statistically significant behavioral change, they provide a critical foundation upon which more interactive, practice-oriented, and longitudinal interventions can build.

VI. Conclusion and Future Work

This study investigated the effects of a video-based learning module on cybersecurity awareness and self-reported behavior among first-semester students in non-technical degree programs.

With respect to *RQ1*, the results confirm that students entered the course with limited prior exposure to formal cybersecurity education and only moderate baseline awareness. Although many participants reported familiarity with selected security concepts, the pre-test results revealed inconsistencies in secure everyday behaviors, particularly in areas, such as password re-use and online risk assessment. These findings align with prior research indicating that higher education students often overestimate their cybersecurity competence despite existing behavioral vulnerabilities.

Regarding *RQ2*, the pre/post comparison shows that the video-based intervention contributed to increased cybersecurity awareness and improved recognition of common threats, most notably phishing. While descriptive trends indicate small but consistent improvements in several behavioral indicators, the statistical analysis did not reveal significant overall changes. This suggests that the intervention primarily supported awareness raising and reflective engagement rather than immediate behavioral transformation.

Future work should therefore extend the observation period, integrate hands-on and scenario-based learning components, and account for individual baseline differences when evaluating intervention effects. Longitudinal studies could further examine whether repeated or scaffolded video-based interventions lead to measurable behavioral change over time. Overall, the results provide valuable guidance for designing effective cybersecurity awareness programs in higher education and highlight the importance of combining digital content with active learning strategies.

Additionally, future research should explore domain-specific adaptations of cybersecurity awareness interventions. Rather than addressing cybersecurity as a broad and abstract concept, targeted modules focusing on specific domains (e.g., healthcare, critical infrastructure, or finance) may increase relevance and behavioral transfer. Learners operating within a familiar domain context are more likely to connect educational content with real-world consequences. Thereby strengthening the transition from awareness to action. Such domain-specific approaches may also enable the transfer of lessons learned from prior incidents ("known bad outcomes") into actionable behavioral patterns within the learners' own professional or academic environments.

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Evolution of Educational Gamification Design: From Points-Based Systems to AI-Enhanced Narrative Integration

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***Abstract*— Educational gamification has evolved through three distinct phases: points-badges-leaderboards (PBL) dominance (pre-2017), narrative integration (2015-2024), and AI-enhanced design (2023-present). This paper asks: does the shift toward narrative and AI-enhanced design actually improve learning outcomes, and do those effects hold across integration methods? Drawing on a systematic review of 39 studies and empirical data from four course implementations (N = 635), we find that narrative gamification correlates with significant learning gains (+4-5%, d = 0.27-0.32) and 65-89% student approval. Critically, AI-generated narrative content proves most effective when invisibly embedded in course design (66-73% undetectable) rather than surfaced as explicit AI communication (33% undetectable). This evolution represents an evidence-based progression reducing technical barriers for educators while introducing new ethical obligations around transparency and oversight.**

Keywords- Gamification; Educational design; Artificial Intelligence (AI); Narrative learning; Generative AI; Self-Determination Theory (SDT); Constructivism.

I. INTRODUCTION

Educational gamification, applying game design elements in learning contexts, has undergone substantial transformation since mainstream adoption. Early implementations (pre-2017) relied predominantly on Points, Badges, and Leaderboards (PBL) [1]. Research revealed limitations, prompting shifts toward narrative and storytelling [2][3], and generative AI tools (2023-2024) have since created new possibilities for narrative creation [4][5]. This paper traces this evolution through three phases, grounded in Constructivism [9], Self-Determination Theory (SDT) [10], and Engagement Theory [11].

The rest of this paper is organized as follows. Section II presents the three-phase evolution overview. Section III describes Phase I, Section IV addresses Phase II, and Section V, Phase III. In Section VI, we describe the implications for practice. We conclude the article in Section VII.

II. THREE PHASE EVOLUTION OVERVIEW

Table I summarizes the three phases, distinguishing literature-derived evidence from the authors' own implementation findings.

TABLE I. THREE-PHASE GAMIFICATION EVOLUTION

Phase	Characteristics & Limitation	Evidence Source
Phase I: PBL (pre-2017)	Structural overlay; technical simplicity. Limitation: inconsistent outcomes; "pointsification".	Literature [1][2][6]
Phase II: Narrative (2015-2024)	Narrative transforms content; SDT-aligned. Limitation: high implementation burden.	Lit. [1][7] **Authors:** N=448
Phase III: AI-Enhanced (2023-present)	AI creates narrative assets; reduces barriers. Limitation: transparency, ethics, oversight.	Lit. [4][5] **Authors:** N=635

III. PHASE I: PBL DOMINANCE (PRE-2017)

A. Implementation Advantages

PBL elements offered technical simplicity, direct parallels to traditional assessment, and minimal redesign requirements, enabling rapid adoption [1]. From an SDT perspective [10], PBL addresses competence through achievement signals but neglects autonomy and relatedness — the needs most associated with sustained intrinsic motivation.

B. Research Limitations

Research revealed inconsistent learning outcomes. Balci et al. [6] conducted controlled experiments (n = 102; n = 88) finding badges and leaderboards did not improve academic performance despite increased reported motivation — consistent with constructivist critiques of passive structural overlays [9]. By 2015-2017, critique of "pointsification" identified core problems: points losing meaning,

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leaderboards creating harmful competition, and rewards disconnected from learning [2].

IV. PHASE II: NARRATIVE INTEGRATION (2015-2024)

A. Theoretical Distinction and Literature Evidence

Research distinguishes structural gamification (PBL overlay on unchanged content) from content gamification (narrative transforms content itself), grounded in Constructivist Theory [9]. Khaldi et al. [1] reviewed 39 studies, finding 20 (51%) incorporated narrative elements. Jarrah et al. [7] examined 500 students and found narrative variables the strongest predictor of skill acquisition, followed by gamified engagement. Narrative design aligns with SDT [10] by providing meaningful context (relatedness) and learner choice (autonomy), and with Engagement Theory [11] through collaborative, project-based frameworks.

B. Authors' Implementation Data

The following findings derive from the authors' implementations, not the literature review. Narrative was operationalized through thematic framing: all course materials, assessments, and assignments were reframed within a coherent storyline (Mario Party-themed), with structured narrative progression across the semester and role-based participation elements. A quasi-experimental comparison of Fall 2023 versus Fall 2024 sections of the same undergraduate psychology course (same instructor, institution, and assessments; $N = 448$ across three sections) introduced this narrative gamification while holding all other variables constant. Results showed significant improvements across three standardized assessment domains: math performance +4.3% ($t(378) = 2.87$, $p = .004$, $d = 0.29$), theory understanding +3.8% ($t(378) = 2.63$, $p = .009$, $d = 0.27$), and lab skills +4.2% ($t(378) = 2.75$, $p = .006$, $d = 0.28$). Each domain was assessed by a standardized instrument tied to course content delivered under the Mario Party narrative: math performance via weekly problem sets framed as mini-game challenges, theory understanding via scenario-based quizzes embedded in the storyline, and lab skills via practical exercises presented as in-game tasks. These gains are promising but should be interpreted cautiously: as a quasi-experimental design, novelty effects, instructor enthusiasm, or unmeasured cohort differences cannot be fully ruled out. Visual gamification elements received 65-89% student approval; 76% reported reduced anxiety and 75% found assignments more enjoyable, consistent with SDT's relatedness and competence dimensions [10].

V. PHASE III: AI-ENHANCED DESIGN (2023-PRESENT)

A. Addressing Technical Barriers — Literature Evidence

Narrative implementation remained technically demanding. Wei et al. [4] conducted a 20-week experiment ($n = 60$) comparing AI-assisted digital storytelling (ChatGPT, Midjourney, Runway) versus conventional approaches; the AI group showed significantly enhanced collaborative problem-solving and creativity. De Vicente-Yagüe-Jara et al. [5] found ChatGPT improved creative writing fluency, flexibility, and originality in 193 students, while emphasizing AI functions best as collaborative assistant, not replacement for human judgment.

B. Integration Method Matters — Authors' Implementation Data

The following findings derive from the authors' four course implementations ($N = 635$). A direct comparison examined two AI integration strategies: (1) embedded AI, in which AI-generated content formed invisible narrative infrastructure (Mario Party/Pokemon themes woven into course materials), and (2) explicit AI, in which AI-generated text appeared as direct course communications. The results are summarized in Table II.

TABLE II. AI INTEGRATION METHOD COMPARISON (Authors' Data, N = 635)

Outcome Measure	Embedded AI (n=448)	Explicit AI (n=187)
Undetectable as AI	66-73%	33%
Added educational value	49-72%	32-44%
Natural and engaging	61-72%	Not assessed

Note. N/A = not assessed in explicit AI condition.

VI. IMPLICATIONS FOR PRACTICE

A. Evidence-Based Design

Educators should prioritize narrative-integrated gamification over PBL-only approaches. Visual gamification elements receive 65-89% approval with learning gains of $d = 0.27\text{-}0.32$, small-to-medium effect sizes representing meaningful educational improvement.

B. Strategic AI Integration

Employ AI as invisible narrative infrastructure rather than an explicit course "voice." Embedded AI significantly outperforms explicit AI on detectability (66-73% vs. 33%) and perceived value (49-72% vs. 32-44%). Theme selection should map deliberately to learning objectives: for example, Mario Party's mini-game structure maps naturally to distinct skill domains (math, theory, lab), enabling themed assessments that reinforce specific competencies rather than applying a generic overlay.

C. Transparency, Ethics, and Human Oversight

The effectiveness of invisible AI integration creates an inherent ethical tension: students consistently express concerns about accuracy and over-reliance [8], and agency requires some awareness of the tools shaping their learning environment. We propose a *transparency with boundaries* framework that preserves engagement benefits while respecting student agency: (1) **disclose at the syllabus level** that AI tools support course design, without foregrounding specific implementations; (2) **maintain explicit human**

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control over all pedagogical objectives, assessment criteria, and quality assurance — educators review and curate all AI-generated content before deployment; (3) **model critical AI evaluation** as a transferable skill by periodically inviting students to assess AI-generated content for accuracy and bias; and (4) **set clear boundaries** distinguishing instructor-authored content from AI-assisted infrastructure. This framework acknowledges AI's role without obscuring it entirely, reducing the risk of over-reliance while preserving the engagement advantages of embedded narrative.

D. Limitations

Several limitations should be noted. First, all implementations were quasi-experimental rather than randomized; novelty effects, instructor enthusiasm, and unmeasured cohort differences cannot be excluded. Second, all data derive from a single institution and discipline (undergraduate psychology, UCF), limiting generalizability. Third, student approval ratings are self-reported and subject to social desirability bias. Fourth, the URM classification in student samples aggregates groups with potentially different responses to gamification elements. Future work should employ randomized designs, validated engagement instruments, and multi-institution samples.

VII. CONCLUSION

Educational gamification has evolved from PBL systems through narrative integration to AI-enhanced design. Narrative gamification produces measurable learning gains (4-5%, $p < .01$, $d = 0.27$-0.32) and strong student approval (65-89%), grounded in Constructivism [9], SDT [10], and Engagement Theory [11]. AI tools enable sophisticated narrative creation at scale, but effectiveness depends critically on method: embedded narratives substantially outperform explicit AI communications. Provided educators maintain transparent human oversight, this evolution creates unprecedented opportunity to implement research-validated narrative approaches without technical barriers.

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One Size Fits None: Why AI Distrust in Education Depends on Who You Ask

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Abstract — **Adaptive learning systems and AI-powered educational tools are increasingly deployed across diverse student populations, yet they are typically designed and validated with majority students and assumed to work uniformly for all learners. We extend algorithmic bias concerns to the psychological level: if the mental processes by which students form AI trust differ across cultural backgrounds, seemingly neutral design choices may inadvertently widen achievement gaps. Using data from over one thousand university students at a Hispanic-Serving Institution, we find that the anthropomorphism paradox, the counterintuitive finding that viewing technology as human-like predicts lower AI trust, operates robustly among non-UnderRepresented Minority (non-URM) students but is entirely absent among URM students, despite both groups showing identical mean levels of anthropomorphism and AI trust. Additionally, students who received smartphones before age 16 show meaningfully stronger superstitious beliefs and lower AI trust than later adopters. These findings reveal that cultural background and developmental technology exposure create fundamentally different psychological pathways to AI trust, with direct implications for designing equitable adaptive learning systems.**

Keywords- educational AI; adaptive learning; AI trust; anthropomorphism; educational equity; personalized learning; cultural moderation.

I. Introduction

The Problem: One-Size-Fits-All AI in Diverse Classrooms

Adaptive learning systems and AI-powered educational tools are rapidly becoming standard infrastructure in higher education. Students interact with AI tutors for homework help, receive personalized content recommendations from adaptive platforms, and obtain automated feedback on written work. These systems promise to democratize access to high-quality, individualized instruction at scale, a vision particularly compelling for large public universities serving economically and culturally diverse student populations.

Yet this promise rests on the largely untested assumption that all students respond to AI features in psychologically similar ways. When educational AI systems are designed and validated primarily with majority student populations, then deployed universally without considering cultural or developmental diversity, they risk creating unequal psychological barriers that undermine the very equity goals they aim to serve.

A. Why This Matters: Equity Beyond Access

The digital divide has traditionally focused on access, whether students have devices, connectivity, and technical skills. But equity in educational AI requires more than equal access; it requires that the psychological architecture of these systems works equitably for all learners. If design features that enhance trust and engagement for majority students simultaneously create barriers for UnderRepresented Minorities, then widespread AI deployment may inadvertently widen rather than close achievement gaps.

Recent evidence suggests this concern is not hypothetical. Algorithmic bias research has documented that automated systems consistently produce differential outcomes for Black, Hispanic/Latino, and other UnderRepresented Minority (URM) students, even when systems appear technically neutral [2][3]. These disparities emerge not only from biased training data but from the interaction between system design and diverse user populations. We propose that an analogous phenomenon operates at the psychological level: the mental processes by which students form trust in AI may differ fundamentally across cultural backgrounds, making ostensibly neutral design choices, such as conversational interfaces or anthropomorphic features, inequitable in practice.

B. The Research Gap: Do Trust Mechanisms Generalize?

Prior research has established what we term the “anthropomorphism paradox:” students who attribute human-like qualities to technology (e.g., believing “the computer hates me”) paradoxically report lower rather than higher trust in AI systems [4]. This counterintuitive pattern is rooted in superstitious thinking: students with stronger beliefs about bad luck and unpredictable forces anthropomorphize technology more, and that anthropomorphism erodes AI trust.

However, virtually all evidence for this pathway comes from aggregate analyses that implicitly assume uniform psychological mechanisms across all students. No prior research has tested whether the anthropomorphism paradox operates identically for UnderRepresented Minority (URM) and non-UnderRepresented Minority (non-URM) students, nor whether the developmental timing of technology exposure shapes these trust formation processes.

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C. Research Questions and Contributions

This paper addresses two questions with direct implications for adaptive learning system design:

Hypothesis 1 (Cultural Moderation): Does the anthropomorphism paradox operate uniformly, or does it differ between UnderRepresented Minority (URM) and non-UnderRepresented Minority (non-URM)?

Hypothesis 2 (Developmental Timing): Does the age at which students first accessed smartphones predict the superstitious beliefs and AI trust they bring to educational AI systems?

Our contributions are threefold:

1. Theoretical: We demonstrate that the anthropomorphism paradox is culturally bound rather than universal, operating robustly among non-URM students but being entirely absent among URM students, despite both groups showing identical mean levels of anthropomorphism and AI trust. This "moderation without mean differences" pattern is invisible to aggregate analyses and represents a novel finding in educational technology research.

2. Developmental: We provide the first empirical evidence that early smartphone access (before age 16) predicts lasting differences in superstitious thinking and AI trust, with medium-sized effects. This finding is particularly timely given recent policy debates in Spain, Greece, and other nations about restricting youth access to algorithmic systems.

3. Practical: We offer actionable design principles for adaptive learning systems, emphasizing the need for configurable interaction styles, disaggregated evaluation metrics, and AI literacy scaffolding that addresses superstition-based anthropomorphism.

II. Related Work

A. Anthropomorphism and Technology Trust

Anthropomorphism, attributing human characteristics, emotions, or intentions to non-human entities, is a fundamental feature of human cognition that varies systematically across individuals and situations [1]. Epley et al. [6] proposed a three-factor theory identifying psychological determinants: the accessibility of anthropocentric knowledge, motivation to understand agent behavior (effectance motivation), and desire for social connection (sociality motivation). These factors predict when people see nonhuman agents, including AI systems, as possessing human-like minds.

In educational contexts, anthropomorphism has emerged as a significant driver of student attitudes toward AI tools. Polyportis and Pahos [7] found that anthropomorphism, alongside trust and perceived novelty, predicts AI chatbot adoption among university students. However, the relationship between anthropomorphism and trust is not straightforward. Jose and Thomas [8] highlighted that digital anthropomorphism shapes epistemic trust in AI tutors in complex ways not yet well understood, particularly for underrepresented learners who may calibrate trust based on different cues than majority students.

1) The Anthropomorphism Paradox

Recent research has revealed a counterintuitive pattern: attributing human-like qualities to AI can reduce rather than enhance trust. Janowsky and Hubertz [4] documented that students who anthropomorphize technology, viewing computers as capable of "hating" users or "seeing all", report lower trust in AI systems. This "anthropomorphism paradox" challenges the widespread assumption in educational technology design that making AI seem more human-like universally improves acceptance and engagement.

The psychological origins of this paradox lie in superstitious thinking. Risen [5] demonstrated that superstitious beliefs persist even when individuals cognitively recognize them as irrational, suggesting they reflect deep-seated intuitive processes rather than simple ignorance. Students high in beliefs about bad luck and unpredictable forces [9] anthropomorphize technology more, experiencing AI systems as unpredictable social agents rather than controllable tools.

B. Superstitious Beliefs and Locus of Control

Fluke and colleagues [9] developed the Belief in Superstition Scale (BSS), demonstrating that superstitious beliefs cluster into three distinct components: belief in bad luck, belief in good luck, and belief that luck can be changed. Critically, they found that external locus of control, the belief that life outcomes are determined by forces beyond personal control, consistently predicts all three types of superstitious beliefs.

The connection between superstition and technology attitudes suggests a hierarchical pathway: external locus of control predicts superstitious beliefs, which predict anthropomorphic interpretations of technology, which in turn predict trust in AI systems. However, this pathway has only been documented in aggregate samples, leaving open the question of whether it operates uniformly across diverse student populations.

C. Algorithmic Bias and Educational Equity

Research on algorithmic bias has documented extensive evidence that automated systems often produce discriminatory outcomes for minority populations. Buolamwini and Gebru's [10] landmark "Gender Shades" study revealed that commercial facial recognition systems showed error rates up to 34.7% for darker-skinned females while achieving near-perfect accuracy (0.8% error) for lighter-skinned males.

In educational contexts specifically, Baker and Hawn [2] found that across predictive models, AI-powered assessments, and recommendation engines, algorithms consistently produced differential outcomes for Black, Hispanic/Latino, and other URM students. Gándara et al. [3] documented that predictive models used in college student-success systems produced false negatives for 19% of Black students and 21% of Latinx students, systematically under-identifying learners they were designed to support.

These documented experiences with algorithmic bias may fundamentally shape how different student populations calibrate trust in AI systems. If URM students have observed algorithmic systems disadvantaging their communities in practice, their trust formation mechanisms may prioritize factors like perceived fairness, transparency, and historical reliability over anthropomorphic features.

D. *The Critical Gap: Universal Mechanisms Assumption*

Despite evidence of algorithmic bias and differential system performance across student populations, research on the psychological mechanisms underlying AI trust continues to assume universal processes. Studies documenting relationships between anthropomorphism, superstition, and technology trust have examined aggregate patterns without testing for moderation by race, ethnicity, or other diversity dimensions.

Similarly, developmental psychology research suggests that timing of technology exposure during formative periods may shape lasting attitudes toward digital systems, yet no prior work has examined whether age of first smartphone access predicts AI trust in educational contexts.

Our study addresses these gaps by testing whether the anthropomorphism paradox operates uniformly across URM and non-URM students, and whether developmental timing of smartphone access shapes superstitious beliefs and AI trust.

III. METHODS

A. *Study Design Overview*

We conducted a cross-sectional survey study to test two primary hypotheses: (1) that the relationship between technology anthropomorphism and AI trust differs between UnderRepresented Minority (URM) and non-URM university students (cultural moderation hypothesis), and (2) that age of first smartphone access predicts superstitious beliefs and AI trust in young adulthood (developmental timing hypothesis).

The study employed a correlational design with both continuous and categorical predictor variables. Cultural background (URM vs. non-URM) and smartphone access timing (before vs. at/after age 16) served as moderator variables, while technology anthropomorphism, superstitious beliefs, and AI trust were measured as continuous outcome variables. We also examined the hierarchical pathway from external locus of control through superstitious beliefs to anthropomorphism to AI trust, testing whether this pathway operates similarly across cultural groups.

Data collection occurred during Fall 2023 through Spring 2024 via an online survey platform. The study was approved by the University of Central Florida Institutional Review Board (protocol #STUDY00005234), and all participants provided informed consent before beginning the survey.

B. *Participants*

1) *Sample Characteristics*

Participants were 1,331 undergraduate students enrolled at the University of Central Florida (UCF), a large public research university and designated Hispanic-Serving Institution in Orlando, Florida. UCF enrolls approximately 69,000 students and is one of the most diverse universities in the United States, making it an ideal context for examining cultural moderation in educational technology attitudes.

Of the initial 1,331 participants, 1,306 (98.1%) completed all measures and passed embedded attention checks, forming the final analytic sample. The sample was predominantly female (60.4% female, 38.1% male, 1.5% non-binary or other) with a mean age of 19.48 years (SD = 3.44, range 18–47). First-generation college students, those whose parents did not complete a four-year college degree, comprised 35.2% of the sample, reflecting UCF's mission to serve diverse student populations.

2) *Cultural Background Classification*

For cultural moderation analyses, participants were classified into two groups based on self-reported race/ethnicity. UnderRepresented Minority (URM) students (n = 234, 17.9%) identified as Black/African American, Hispanic/Latino, Native American, Pacific Islander, or multiracial with at least one URM component, aligning with standard definitions in higher education research and federal reporting. Non-URM students (n = 1,072, 82.1%) identified as White and/or Asian. This classification reflects the documented finding that Asian students in STEM and higher education contexts do not face the same systemic barriers as other minority groups, though we acknowledge this remains a debated categorization.

We recognize that the URM category aggregates diverse ethnic and cultural groups whose relationships with algorithmic systems likely differ. This aggregation was necessary given sample size constraints but represents a limitation we address in the Discussion.

3) *Smartphone Access Timing*

Participants reported the age at which they first owned or had regular access to a smartphone. Responses ranged from age 5 to age 25, with a mean of 12.30 years (SD = 2.30). For primary analyses, we dichotomized this variable as early access (before age 16; n = 1,235, 94.6%) or late access (at or after age 16; n = 71, 5.4%). The age-16 threshold was selected based on two considerations: (1) it aligns with current policy debates in Spain, Greece, and other nations considering social media age restrictions, and (2) it corresponds to mid-adolescence, a developmentally sensitive period for forming abstract reasoning about agency and causality. We also conducted supplementary analyses treating smartphone access age as a continuous variable to examine dose-response relationships.

C. *Measures*

All measures used Likert-type rating scales and demonstrated acceptable-to-excellent internal consistency reliability. Internal consistency was assessed using

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Cronbach's alpha (α), a statistical measure of how consistently items within a scale measure the same underlying construct. Alpha values above .70 are generally considered acceptable, above .80 good, and above .90 excellent.

1) Technology Anthropomorphism

Technology anthropomorphism was measured using a 3-item composite drawn from the Technology Superstition Scale [4]. Items were selected specifically to capture attributions of human-like qualities to computers and smartphones: (1) "The computer hates me," (2) "The computer sees all and knows all," and (3) "My phone sees all and knows all." Participants rated their agreement on a 5-point scale (1 = Strongly Disagree to 5 = Strongly Agree). Items were averaged to create an overall anthropomorphism score (α = .82). These items capture attributions of intentionality, omniscience, and agency to technological devices — distinct from general anthropomorphism scales by their focus on magical or superstitious thinking about technology possessing human-like awareness.

2) Superstitious Beliefs

Superstitious beliefs were assessed using the 18-item Belief in Superstition Scale (BSS; [9]), consisting of three 6-item subscales. The *Bad Luck subscale* (α = .85) measures beliefs that certain actions or events bring negative outcomes (e.g., "Breaking a mirror brings bad luck," "Friday the 13th is an unlucky day"). The *Good Luck subscale* (α = .89) measures beliefs that certain objects or actions bring positive outcomes. The *Change Luck subscale* (α = .76) measures beliefs that one can actively manipulate luck. Participants rated each item on a 7-point scale (1 = Strongly Disagree to 7 = Strongly Agree); the overall BSS demonstrated excellent internal consistency (α = .90). We focused primarily on Bad Luck beliefs given their theoretical relevance to threat-oriented anthropomorphism. Fluke and colleagues [9] demonstrated that Bad Luck beliefs correlate most strongly with neuroticism and external locus of control, whereas Good Luck beliefs correlate with agreeableness and Change Luck beliefs with proactive coping.

3) AI Trust

Trust in artificial intelligence was measured using a 16-item scale covering four conceptual domains: (1) *Security/Privacy* — trust that AI systems protect personal information and maintain confidentiality (4 items); (2) *Validity/Reliability* — trust that AI systems produce accurate and consistent outputs (4 items); (3) *Capability* — trust that AI systems can successfully perform intended tasks (4 items); and (4) *Understandability* — trust that AI system operations are transparent and comprehensible (4 items). Example items include "I trust AI to keep my personal information secure," "I trust AI to provide reliable recommendations," and "I trust AI to accurately assess my work." Participants rated each item on a 7-point scale (1 = Strongly Disagree to 7 = Strongly Agree). Items were averaged to create an overall AI trust score (α = .91), indicating the four domains cohere into a unified construct. This multidimensional measure is particularly appropriate for educational contexts, where students must trust AI systems across multiple functions.

D. Procedure

Participants were recruited through the UCF Psychology Department's research participation system and received course credit for participation. The survey was administered online via Qualtrics and required approximately 25–30 minutes to complete. After providing informed consent, participants completed measures in a fixed order: (1) demographic questions, (2) smartphone access timing, (3) superstitious beliefs (BSS), (4) technology anthropomorphism, (5) AI trust, (6) external locus of control, and (7) embedded attention checks. Fixed order was used to prevent exposure to AI trust items from priming technology-related superstitious thinking.

Three attention check items were embedded throughout the survey (e.g., "Please select 'Strongly Agree' for this item"). Participants who failed two or more attention checks were excluded from analyses (n = 25, 1.9% of initial sample). Upon completion, participants were debriefed about the study's purpose and provided with resources for learning about AI literacy and educational technology.

E. Analytic Approach

All analyses were conducted in SPSS. For cultural moderation analyses (Hypothesis 1), we computed separate Pearson correlation coefficients for URM and non-URM students, then tested for differences using Fisher's r-to-z transformation. For developmental timing analyses (Hypothesis 2), we compared early-access and late-access groups using independent-samples t-tests with Welch's correction for unequal variances. Effect sizes were computed using Cohen's d for group comparisons and interpreted using conventional benchmarks (small: d = 0.20, medium: d = 0.50, large: d = 0.80). Missing data were minimal (<2% for any single variable) and addressed through listwise deletion. Alpha was set at .05 for all tests, with exact p-values reported for transparency.

IV. Results

A. The Paradox Is Not Universal: Cultural Moderation

Technology anthropomorphism predicted lower AI trust in the overall sample ($r = -.14$, $p < .001$). Critically, however, both groups showed nearly identical mean levels of anthropomorphism (M non-URM = 3.04 vs. M URM = 3.10, $d = -0.04$) and AI trust (M non-URM = 4.33 vs. M URM = 4.27, d = 0.06), yet the relationship between these constructs differed fundamentally (see Table I).

Among non-URM students (n = 1,072), anthropomorphism was a robust negative predictor of AI trust ($r = -.155$, $p < .001$, 95% CI [−.213, −.096]). To interpret this correlation: for every one standard-deviation increase in anthropomorphism among non-URM students, AI trust decreased by approximately 0.15 standard deviations. This replicates the expected "anthropomorphism paradox" — viewing technology as more human-like predicts lower trust in AI. The narrow confidence interval that does not include zero confirms this is a reliable effect.

TABLE I. ANTHROPOMORPHISM–AI TRUST CORRELATIONS BY URM STATUS

Group	*n*	*r*	*p*	95% CI
Non-URM	1,072	−.155	< .001	[−.213, −.096]
URM	234	.021	.754	[−.108, .148]
Group difference (Fisher's $Z = -2.44$)			.015	—

Note. URM = UnderRepresented Minority. Non-URM = White and/or Asian students. CI = confidence interval.

Among URM students (n = 234), the same relationship was near-zero and non-significant (r = .021, p = .754, 95% CI [−.108, .148]). This correlation is essentially zero, and the wide confidence interval that crosses zero indicates there is no relationship between anthropomorphism and AI trust for URM students. Using Fisher's r-to-z transformation, which converts correlations to a common scale for comparison, we confirmed that the two groups differ significantly ($Z = -2.44$, p = .015).

Table I presents these core moderation findings. The confidence intervals provide additional evidence: the non-URM interval [−.213, −.096] excludes zero entirely, while the URM interval [−.108, .148] comfortably includes zero, confirming these are genuinely different patterns rather than merely weaker versions of the same effect.

This pattern, identical means but different relationships, reveals "moderation without mean differences." Both groups anthropomorphize technology to the same degree and trust AI at the same level on average. However, the psychological significance of anthropomorphism differs fundamentally: for non-URM students, viewing technology as human-like signals unpredictability and reduces trust; for URM students, these beliefs are psychologically unrelated to trust formation.

The correlation between bad luck beliefs and technology anthropomorphism operated similarly across groups (Non-URM: r = .293, p < .001; URM: r = .228, p = .001; Fisher's Z = 0.96, p = .336), indicating that the pathway from superstitious thinking to anthropomorphic technology beliefs does not differ by cultural background. The divergence emerges at the next step: what those anthropomorphic beliefs mean for AI trust.

B. *Growing Up Algorithmic: Developmental Timing*

Early smartphone access was nearly universal: 94.6% of students (n = 1,235) received their first smartphone before age 16 (M = 12.30 years, SD = 2.30); 48.6% gained access during elementary or middle school (ages 10–12). Despite small cell sizes, comparisons with late-access students (age ≥ 16; n = 71) revealed medium-sized effects across all three outcome variables (Table II).

Students who received smartphones before age 16 reported significantly stronger beliefs in bad luck (M = 28.86, SD = 8.84 vs. M = 25.79, SD = 9.48), $t(78.33)$ = 2.65, p = .010, Cohen's d = 0.35. To contextualize this effect: the difference between early and late-access groups is approximately one-third of a standard deviation, translating to moving from the 50th percentile to approximately the 64th percentile in bad luck beliefs. This medium-sized effect suggests that early exposure to unpredictable algorithmic systems may shape enduring beliefs about uncontrollable forces in technology.

Students with early smartphone access also reported meaningfully lower AI trust (M = 4.32, SD = 0.88 vs. M = 4.60, SD = 1.03), $t(76.74) = -2.28$, p = .026, $d = -0.32$. On a 7-point scale, the 0.28-point difference represents approximately one-third of a standard deviation, a meaningful shift that could influence how students engage with educational AI throughout their university careers. Notably, this effect size ($d = -0.32$) is comparable to the bad luck effect (d = 0.35), suggesting that developmental timing has similarly strong impacts on both superstitious thinking and AI trust.

The difference in anthropomorphism did not reach conventional statistical significance (M = 3.05, SD = 1.01 vs. M = 2.85, SD = 1.07), $t(77.05)$ = 1.54, p = .129, d = 0.20, though the effect size falls in the small-to-medium range and trends in the expected direction. The lack of statistical significance likely reflects the small late-access sample size (n = 71), which limits statistical power to detect small-to-medium effects.

Continuous analyses showed earlier access predicted stronger bad luck beliefs ($r = -.171$, p < .001) and greater anthropomorphism ($r = -.124$, p < .001), while the correlation with AI trust was near-zero (r = .030, p = .277), suggesting the trust effect operates as a developmental threshold rather than a linear gradient. The pattern where the categorical comparison (before vs. at/after age 16) yields significant effects on trust (p = .026) but the continuous correlation does not (p = .277) supports the interpretation that age 16 represents a critical developmental boundary rather than part of a smooth continuum.

TABLE II. KEY OUTCOMES BY AGE OF FIRST SMARTPHONE ACCESS

Outcome	Early (<16) M (SD)	Late (≥16) M (SD)	*t*	*p*	*d*
Bad Luck Beliefs	28.86 (8.84)	25.79 (9.48)	2.65	.010	0.35
AI Trust	4.32 (0.88)	4.60 (1.03)	−2.28	.026	−0.32
Anthropomorphism	3.05 (1.01)	2.85 (1.07)	1.54	.129	0.20

Note. Values are M (SD). Welch's correction applied for unequal variances. n early = 1,235; n late = 71.

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V. DISCUSSION

A. The Paradox Has Boundaries

The anthropomorphism paradox is not a universal psychological mechanism. As demonstrated in Table I, it operates robustly among non-URM students ($r = -.155$, $p < .001$) but is entirely absent for URM students ($r = .021$, $p = .754$), despite both groups showing nearly identical mean levels of anthropomorphism and AI trust. This is exactly the kind of subgroup effect invisible to aggregate analyses, and it has a direct consequence for learning analytics: institutions monitoring average AI trust or average system engagement across student populations will see no equity problem. The problem is in the relationship structure underneath those means.

The statistical evidence in Table I is compelling: the Fisher's Z test confirms that these correlations differ significantly ($Z = -2.44$, $p = .015$), and the non-overlapping confidence intervals reinforce that this is a genuine moderation effect rather than measurement noise. We propose that URM students employ fundamentally different trust calibration strategies that are orthogonal to anthropomorphism. Trust for these students may depend more on perceived fairness, cultural representation, transparency, and historical reliability, all factors shaped by documented experiences with algorithmic bias in high-stakes domains [2][3]. When automated systems have disadvantaged one's community in practice, the question of whether a computer personally "hates" you may be psychologically irrelevant; trust is calibrated on different criteria entirely. For non-URM students, whose cultural contexts may emphasize individual predictability and control, an anthropomorphized AI becomes a potential social adversary, perceived as unpredictable and evaluative, triggering the distrust effect.

B. Early Smartphone Exposure Has Lasting Consequences

The 94.6% of students who received smartphones before age 16 enter university carrying stronger superstitious bad luck beliefs and lower AI trust than peers with later access, representing medium-sized effects ($d \approx 0.32$–0.35) that are not trivial. Table II reveals the specific pattern: early-access students score nearly one-third of a standard deviation higher on bad luck beliefs and one-third of a standard deviation lower on AI trust compared to late-access peers. Students who encountered recommendation algorithms, social media content curation, and AI-driven interfaces during developmentally sensitive periods appear to have formed mental models of technology that are less trusting and more infused with magical thinking.

For adaptive learning system designers, this matters: nearly the entire incoming student cohort is carrying a trust deficit shaped by their pre-university algorithmic experiences. The threshold pattern shown in Table II, where the categorical comparison (before vs. after age 16) yields significant effects on bad luck beliefs ($p = .010$) and AI trust ($p = .026$) while continuous analyses show weaker linear relationships, aligns with developmental research identifying mid-adolescence as a critical period for forming abstract reasoning about agency and causality, suggesting that early exposure shapes deep cognitive frameworks, not just surface attitudes.

C. Design Implications

Together, these findings (Tables I and II) expose the cost of one-size-fits-all educational AI design. Anthropomorphic features are typically justified by evidence from majority populations that they increase engagement. But if anthropomorphism reduces trust for non-URM students while being neutral for URM students (Table I), then the same design choice creates differential barriers to AI engagement, potentially widening achievement gaps even as educators intend the opposite. Similarly, the developmental timing effects in Table II suggest that current students arrive at university with baseline trust levels already shaped by childhood algorithmic exposure, meaning that educational AI systems must account for this pre-existing trust deficit rather than assuming a blank slate.

Three principles follow:

1. **Build adaptability in from the start.** Offer configurable interaction styles, either conversational and personality-rich for students who benefit, or neutral and function-focused for others, driven by student preference, not demographic assumptions.
2. **Disaggregate evaluation data.** Average engagement metrics mask real subgroup differences. As Table I demonstrates, URM and non-URM students can have identical means yet fundamentally different psychological relationships with AI features. Equity-centered evaluations should routinely examine whether AI systems create differential barriers across race/ethnicity, first-generation status, and technology exposure history.
3. **Scaffold AI literacy to address superstition-based anthropomorphism.** Since the superstition → anthropomorphism link is consistent across groups, helping students develop accurate mental models of how AI operates (e.g., pattern recognition, not consciousness) may reduce the anthropomorphic misattributions that drive distrust among non-URM students. Table II suggests this is particularly important given that 95% of students arrive with early algorithmic exposure that has already shaped their beliefs about technology as unpredictable and driven by forces beyond their control.

D. Limitations and Future Directions

Several limitations warrant consideration. The cross-sectional design precludes causal inference: we cannot establish that early smartphone access causes stronger superstitious beliefs and lower AI trust, nor that anthropomorphism causes reduced trust among non-URM students. Unmeasured variables such as parenting style, socioeconomic resources, personality traits, or prior experiences with AI system failures may confound observed relationships. The single-institution sample (a large Hispanic-Serving Institution in the southeastern United

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States) limits generalizability to other institutional contexts, and the 94.6% prevalence of early smartphone access reflects current American college students but may not apply to older cohorts or international populations. Unequal group sizes, particularly for URM students (n = 234) and late smartphone access (n = 71), reduce statistical power for detecting small effects and create less stable estimates for these groups. Additionally, all measures relied on self-report, introducing potential social desirability bias and recall inaccuracy for smartphone access timing, and our AI trust measure assessed trust in "AI" generically rather than specific educational AI applications, which may show different patterns.

The URM classification aggregates Black/African American, Hispanic/Latino, Native American, Pacific Islander, and multiracial students into a single category, masking important heterogeneity in historical relationships with algorithmic systems, cultural values, and experiences with institutional discrimination. The observed null anthropomorphism-trust relationship among URM students may reflect averaging across subgroups with different patterns. Future research should examine specific racial/ethnic groups separately with larger samples, employ longitudinal designs to strengthen causal inference, incorporate behavioral measures of actual AI engagement rather than self-reported trust, test whether AI literacy interventions reduce superstition-based anthropomorphism, and experimentally manipulate anthropomorphic design features to validate recommendations for configurable systems. Intersectional analyses examining how race/ethnicity, gender, socioeconomic status, and first-generation status jointly shape AI trust formation would provide deeper understanding of psychological diversity in educational technology responses.

VI. CONCLUSION

The anthropomorphism paradox is real, but it is not universal, and its boundaries have direct implications for the design and evaluation of adaptive learning systems. Superstitious beliefs about bad luck feed anthropomorphic views of technology across all student groups, but the downstream effect on AI trust applies only to non-URM students; for UnderRepresented Minorities, anthropomorphism and AI trust are psychologically unrelated even when group means are identical. Separately, growing up with smartphones before age 16, which describes the experience of 95% of current students, leaves a lasting imprint: early algorithmic exposure predicts stronger superstitious technology beliefs and lower AI trust in young adulthood, suggesting that students arrive in higher education with meaningfully different baseline readiness for AI-powered learning.

The practical message for learning analytics and adaptive system design is direct: one size does not fit all, and aggregate metrics will not reveal the problem. Institutions deploying AI tutors, intelligent feedback systems, and adaptive curricula must disaggregate trust and engagement data by student population, design for configurability rather than fixed anthropomorphic features, and scaffold AI literacy that helps students develop accurate mental models of how algorithmic systems actually work. Educational equity in the age of AI is not just about access; it is about whether the psychological architecture of these systems works equitably for every learner in the room.

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STEAME Learning with Entrepreneurial Mindset: Implementation in Hybrid Environments

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***Abstract*— This paper addresses STEAME (Science, Technology, Engineering, Arts, Mathematics, and Entrepreneurship) education for both pre-service and in-service teachers, utilizing digital open education resources through blended learning and hybrid environments. The main contributions aim to foster the development of entrepreneurial attitudes and skills through learning and teaching across the whole curriculum using modern technologies in hybrid environments. This approach promotes everyone's entrepreneurial capacity and supports their experiential understanding of the diverse real-world professional context, including its complexity within hybrid environments. Moreover, building the 'can do' mindset through 'hands-on' entrepreneurship experience within the teaching and learning dynamics using interactive multimodal open education resources is emphasized. Additionally, tangible examples, ideas, and tools to inspire and assist educators in planning their own entrepreneurship mindset-based project are provided. Projects such as Sweet Hive Venture, Art Studio/Business, Premium Herbal Wellness and Alpha/Omega Fintech are presented to give a broad view on implementation of STEAME education with an entrepreneurial mindset. Results reflecting the impact of the proposed approaches were obtained for two days training activities in May-October 2025 and are presented to outline some good practices in STEAME education.**

Keywords - Education 4.0; STEAME education; hybrid environments; blended learning; project-based learning.

I. INTRODUCTION

The STEM acronym is used when combining curriculum of science, technology, engineering, and mathematics to elaborate about how things evolve. Although the STEAM approach is relatively recent [1], the idea of integrating science, technology, engineering, and mathematics into educational curricula dates to before 1900. According to [2], STEM integration "traces back to the Morrill Act of 1862, which created land grant universities to promote agricultural science." A few years ago, due to the "Educate to Innovate" Campaign by President Obama, USA has started to prepare 100,000 STEM teachers by 2021 and called for increasing federal funding toward STEM education [3].

STEAM is an expansion of the original acronym STEM, to which "Art" has been added to promote a greater sense of creativity [4]. The "Entrepreneurship" element in STEAME (Science, Technology, Engineering, Arts, Mathematics, and Entrepreneurship) is the catalyst that turns a creative school project into a purposeful innovation, teaching students that their creativity has tangible economic or social value.

The following sections are structured as follows: Section 2 presents the Education 4.0 framework, Section 3 outlines Learning and Creativity Plans (L&CP) from an entrepreneurial perspective, Section 4 describes the implementation details, and Section 5 offers reflections and directions for future work. This educational research suggests that the Entrepreneurship (E) component acts as a connecting element that brings the framework together in a purposeful way.

II. FROM LESSON PLANS TO LEARNING AND CREATIVITY PLANS IN EDUCATION 4.0 FRAMEWORK

A. *Education 4.0 Framework*

The shift from Lesson Plans (LP) to Learning and Creativity Plans (L&CP) marks a departure from "industrialized" education toward a personalized, tech-driven, and student-centric approach. In the STEAME context, this transition is vital because it moves the focus from delivering content to cultivating innovation.

TABLE 1. EDUCATION FRAMEWORKS

Stage	Orientation	Pedagogical approach
Education 1.0	Only memorization, not oriented towards understanding	Teacher-centered; lectures given and memorization tests.
Education 2.0	Communication oriented	Group learning; more interaction but still standardized.
Education 3.0	Knowledge-based	Student-centered; Self-directed learning and early technology.
Education 4.0	Driven by innovation	Focused on AI-powered, personalized, and 21st century-specific core competencies.

Education 4.0 is essentially the educational response to Industry 4.0, the fourth industrial revolution characterized by smart technology, Artificial Intelligence (AI), and the Internet of Things (IoT) [5][6]. In Education 4.0, the teacher is no longer the "sage on the stage" but a facilitator of experiences (see Table 1). The L&CP are focused on the student's journey, not necessarily following a standard curriculum, outlining the environment, the digital tools, and the "open-ended" challenges that allow students to find unique solutions by blending the subjects to mirror real-world problem-solving along S-T-E-M (providing analytical foundation and technical tools), Arts (A) for design, aesthetics and communication, and Entrepreneurship (E).

The most important pillars of Education 4.0 are based on the following facts [5]:

1) Artificial Intelligence (AI) and data analytics allow for *adaptive learning*, where the curriculum adjusts to a student's strengths and weaknesses. If a student understands a concept quickly, they move on; if they struggle, the system provides additional support immediately.

2) Memorization has a lower intensity while the priorities are directed towards *critical thinking* (analysis of facts not only their registration), *creativity* (human-oriented activity, not AI) and *collaboration* (working in hybrid environments).

3) Learning can happen *anywhere, anytime*. This way of thinking is based on *blended learning*, and *mobility-based learning* from classroom to practice spaces or companies, which means also *hybrid environments*. *Flipped classrooms* and *AI-driven tutoring platforms* become the norm in many forward-thinking *schools*.

4) Education 4.0 emphasizes *learning by doing*, which means *Project-Based Learning (PBL).* Instead of just reading about biology, students might use science to simulate an optimization method based on the bees-algorithm. This prepares them for understanding life, society, and their future behavior [6].

5) Education 4.0 instills a *growth mindset*, teaching students how to continuously *upskill* and *reskill* throughout their lives, considering a strong contribution to society and community by *innovation*, and improving *life for all*.

B. Designing L&CP to support STEAME education

The L&CP are typically built on the following five design principles [7]:

1) **Transdisciplinary integration**: How do we provide clean water to a local community? The plan maps out how Science (chemistry of water) and Arts (graphic design for awareness) communicate through a shared language.

2) **The 4D process** (*Discover, Define, Develop, and Deliver)* defines the design thinking process.

3) **Multimodal communication**: The L&CP require students to communicate using Linguistic, Visual, Aural, Gestural, and Spatial skills: Pitching ideas to "investors" as in Entrepreneurship.

4) Designate specific **Reflection Points** where students will communicate their failures and pivots (soft skills), not just their successes.

5) The L&CP should identify a **target audience** beyond the teacher. Whether it is a blog post, a community presentation, or a prototype demo, the communication must be tailored to real stakeholders.

In Education 4.0, the *Entrepreneurship* element turns a student into a *producer* rather than a *consumer.* The L&C Plan must therefore include "*Market Feedback*" loops — teaching students to listen to user's needs and communicate the value proposition of their technical work [7].

According to [7], all L&CP will be composed of sections addressing the following aspects:

- The headings describing the STEAME framework will cover ST/TS cooperation at the stages of the action plan.
- Learning goals and objectives, learning outcomes and expected results, and the proposed methodologies will display the objectives of L&CP.
- Working spaces, the required tools and resources should be specified to support the implementation of the L&CP.
- The implementation phase will define all activities, procedures and reflections, including the project evaluation, reporting and sharing best practices and pivoting points.

III. NEW L&CP IN STEAME EDUCATION

A. Overview

This section describes eight L&CPs designed for use by Student Teachers (ST) and Teachers in Service (TS). In the L&CPs in Table 2, at least two trainers are involved, while in the L&CPs in Table 3, at least three trainers are required to conduct the projects.

TABLE 2. L&CP FOR STUDENT TEACHERS

Project title	Age/Classes	Number of teachers/STEAME domains
Sweet Hive Venture	15-18/10-12	3/*T1(Biology/Agriculture/ Forestry, T2(Math), T3(Entrepreneurship)*
Art Studio	15-18/10-12	3/*T1(History), T2(Art), T3(Entrepreneurship)*
Herbal Wellness	12-15/5-10	3/*T1(Biology), T2(Chemistry), T3(Technologies)*
Alpha Trust Fintech	14-16/10-12	2/*T1(Math), T2(Economics)*

Both ST and TS use games to increase engagement, foster collaboration, and enhance learning across subjects like history, science, and math [8]. Gamification by integration of game-based learning to support STEAME education is a challenging task depending on trainers' competencies, technologies required and the L&CP design.

In the projects above, a total of six hours of study are allocated (typically comprising 4 to 6 activities), involving multiple trainers to interconnect disciplines and highlight their importance for society. For instance, "Art Business" implementation requires a teacher (T4) having strong background in Information and Communication Technologies (ICT) to facilitate the implementation of a small e-commerce platform.

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TABLE 3. L&CP FOR TEACHERS IN SERVICE

Project title	Age/Classes	Number of teachers/STEAME domains
Sweet Hive Venture	15-18/10-12	4/*T1(Biology/Agriculture/ Forestry, T2(Technology) T3(Math), T4(Entrepreneurship)*
Art Business	15-18/10-12	4/ *T1(History), T2(Art), T3(Entrepreneurship), T4(ICT)*
Premium Herbal Wellness	15-18/10-12	4/*T1(Biology), T2(Chemistry), T3(Technologies) T4 (Entrepreneurship)*
Omega Trust Fintech	17-18/11-12	3/*T1(Math), T2(Economics), T3(Entrepreneurship))*

In the following subsections we present short extracts from the L&CPs to illustrate the proposed approach.

B. *Sweet Hive Venture – Developing skills*

In terms of developing critical thinking, problem-solving, and collaboration skills the L&CP should address:

b1. Beekeeping and Sustainability Program

Entrepreneurship	Business planning, marketing, and selling honey and wax products.
Biology	Bee anatomy, life cycle, and pollination process. Sustainable beekeeping practices, biodiversity conservation.
Mathematics	Budgeting, cost analysis, and financial planning.
Parents	Involvement through workshops, honey tasting events, and community engagement.

b2. Mathematics and Data Analysis in Beekeeping:

Entrepreneurship	Using data for informed business decisions.
Biology	Analyzing bee behavior and population trends. Monitoring hive health through data analysis.
Mathematics	Statistical analysis, hive productivity calculations.
Parents	Involvement in data collection and analysis workshops.

b3. Ethical Business Practices and Social Impact:

Entrepreneurship	Integrating ethics into business decision-making.
Biology	Ethical considerations in beekeeping. Measuring and communicating the environmental impact.
Mathematics	Quantifying social and environmental impact.
Parents	Participation in discussions on ethical business practices.

C. *Art Studio/Business – a PBL approach*

The most important aspects in implementing PBL activities are related to Motivation, Methodology, Strategies and Scaffolds. Motivating students to get involved in “Art Studio/Business” project was achieved by highlighting various aspects that appeal to their interests, aspirations, and personal development. Some of the most important follows:

c1) Engaging in practical, experiential learning opportunities.

Students can participate in recreating historical events on a postcard to reveal the importance of knowing history in real life.

c2) Developing entrepreneurial skills and business acumen.

Students can learn about running a sustainable business, from product development to marketing, fostering a spirit of entrepreneurship.

c3) Exploring science, technology, engineering, arts, mathematics, and entrepreneurship (STEAME) concepts.

“Art Studio/Business” involves history (painting as a medium for recording and interpreting historical events), art (paintings commissioned to glorify rulers, celebrate military victories, or reinforce religious beliefs), and technology (digital skills-to create online “Art Business”), offering a multidisciplinary STEAME experience.

c4) Exploring creative product development and innovation.

- Designing and creating postcards which reconstruct historical events allows students to express their creativity and innovation in a real-world business setting.
- Designing and building the e-commerce platform for “Art Business”.

c5) Making a positive impact on the local community.

Participating in community engagement events, workshops, and initiatives allows students to contribute to raise awareness about the importance of history and art.

c6) Developing leadership skills and responsibilities.

Students took leadership roles within the program, leading teams, organizing events, and actively contributing to the success of “Art Studio/Business” project.

c7) Building social connections and teamwork skills.

Collaborating with peers, educators, and community members fosters a sense of camaraderie and teamwork, creating a positive social environment.

Participants in “Art Studio/Business” can highlight resumes and college applications, potentially leading to opportunities in history and art studies, business related in the art domain, or related fields.

By emphasizing the above selection of motivations, “Art Studio/Business” L&CP can be viewed like a program that resonates with a diverse range of student interests, encouraging active involvement and a positive learning experience. It guides students through key themes, artists, and historical contexts, encouraging critical thinking, analysis, and discussion.

D. Premium Herbal Wellness – Action Plan Formulation

The objective of this L&CP is to describe how teachers (ST/TS) can approach STEAME education to empower high-school students with entrepreneurial skills by establishing a sustainable "Premium Herbal Wellness" business taking into account aspects like safety, quality, dosage, interaction and appropriate usage of medicinal herbs as supplementary sources for someone health or beauty (by herbal cosmetics).

The following topics are covered by the four teachers involved in projects, formulating hypotheses about the medicinal herbs, their interaction and technical aspects in the context of botany, biochemistry and biotechnologies. Teacher 4 is business oriented.

d1) Activities of Teacher 1:

1. Adapt botany concepts for grade level.
2. Explain Plant Life Cycles, the parts, and the economic value.
3. Present use cases (Skin care/ Anti-aging Treatment/Skin Protection/Antioxidants/Hair care/Essential oil etc.) to treat or prevent disease, to "maintain" health and for cosmetic use.
4. Encourage observation, classification, gender-specific differentiation.

d2) Activities of Teacher 2:

1. Adapt biochemistry concept for grade level.
2. Explain the basic chemical components and the molecules to understand the plants' biochemistry.
3. Encourage observation and experiment.

d3) Activities of Teacher 3:

1. Adapt biotechnology concepts for grade level.
2. Explain the role of biotechnologies for herbs, tools for quality control of herbal products, introduce students to the Phyto pharmacy field and cosmeceuticals.
3. Encourage students to develop a simple medicinal product and measure the basic characteristics.
4. Encourage students to make simple moisturizing cream or perfume.

d4) Activities of Teacher 4:

1. Explain basic entrepreneurship concepts.
2. Discuss global trends in Herbal Market.
3. Push the interest in developing product niches.
4. Discuss regulations and how to certificate a new project.

Common activity: Discuss the opportunity to design a new combination of herbs to increase the immunity of people/new herbal cosmetics for beauty or restoration. Design a strategy to promote the product to set up an entrepreneurial desire for students.

E. Alpha/Omega Fintech - Instructional Activities, Procedures, Reflections

This subsection presents a STEAME PBL proposal involving 3 teachers (T1 - Math, T2 – Economic Science, T3 – Entrepreneurship) working as a team along five activities.

TABLE 4. STEAME PBL FOR FINTECH

Activity	Who	Tasks
1. Introduction to Financial Education	T1	1.1.1 Introducing the students to mathematical calculations needed and to interpretation and meaning. 1.1.2 Introducing basic notions used in financial and actuarial mathematics. 1.1.3 Presenting basic procedures for data processing under statistical mindset. 1.1.4 Incorporating technology to make the learning experience more dynamic.
	T2	1.2.1 Introducing the main notions about budget management. 1.2.2 Describing basic concept of investing and how it can help to raise money over time.
	T3	1.3.1 Introducing the structural organization of an insurance company and the types of insurance agents.
2. Actuarial Mathematics	T1	2.1.1 Explaining the role of actuaries. 2.1.2 Introducing the concept of expected value. 2.1.3 Encouraging students to find an example of risk management in real life.
	T2	2.2.1 Explaining the importance of Insurance. Presenting different types of insurance: health, auto, home, and life. 2.2.2 Providing students with handouts that include real-world actuarial problems and solutions. 2.2.3 Discussing the education and skills needed to become an actuary.
	T3	2.3.1 Explaining the types of services offered by an insurance company/agency.
3. Life Insurance Policy	T1	3.1.1 Introducing the main notions to understand: Risk and insurance 3.1.2 Defining Annuity. 3.1.3 Explaining the main types of Annuities: Fixed Annuities, Variable Annuities, Immediate Annuities, Deferred Annuities.
	T2	3.2.1 Discussing real-life examples. 3.2.2 Inviting a financial planner or insurance agent to speak to the class about their work and answer questions.
	T3	3.3.1 Discussing how to describe Quantities, Change, Benefits, and Structure of the market.

4. Practical Aspects of Life Insurance	T1	4.1.1 Introducing procedures to solve a mathematical problem with help of mathematical software (R/Python programming, Sheets) 4.1.2 Working into small groups. Give each group a scenario (e.g., a car accident, a house fire). Each group decides how much they would pay for insurance and what the insurance would cover. 4.1.3 Discussing each scenario and how insurance helps managing the risk.
	T2	4.2.1 Presenting a short video explaining annuities and their benefits for long-term savings and financial security. 4.2.2 Working into small groups. Give each group fake money and an annuity contract. Let them decide how much money to put into their annuity each month. Simulate a few years and then start paying out the annuity. Show how their decisions affect their pay. 4.2.3 Fostering teamwork by assigning roles in event planning, promotion, and execution.
	T3	4.3.1 Show how to be an insurance agent.
5. Career Paths in Insurance	T1	5.1.1 Discussing the role of an actuary. Actuaries evaluate complex risks and assess the potential financial consequences involved. Typical duties include analyzing statistical data – for example, medical information about people of a particular age group, computer modeling statistics to determine potential risks and to explore ways to reduce them.
	T2	5.2.1 Discussing principles of insurance. Insurers offer indemnity against clients' losses. That is, they provide funds to compensate clients for losses.
	T3	5.3.1 Discussing the difference between banks and insurance companies. 5.3.2 Discussing the benefits and risks for insurance companies and why reinsurance is necessary. 5.3.3 Presenting use cases for insurance/reinsurance in various fields like: pension, accidents and health, life, property and casualty, kidnap and ransom etc.

According to our vision, the student activities are important as well. Some examples of tasks follow:
1. Fill a simple budget template based on a hypothetical income and expenses scenario.
2. Create a simple game with probabilities and outcomes.
3. In small groups, students create a budget for a common scenario (e.g., planning a birthday party within a budget).
4. Discuss and understand the importance of actuarial mathematics.
5. Students are encouraged to discuss how actuaries work in insurance, finance, and other industries to help companies make smart decisions.
6. Design a poster to underline how actuaries might calculate the probability of an event like a car accident or a natural disaster.
7. Understand and discuss the fundamental concepts of insurance and annuities.
8. Make a poster with the risk activities and insurance activities.
9. Create multimedia projects related to insurance and risk management, highlight the projects in school exhibitions or community events.
10. Create a game of insurance business.
11. Play an insurance game.
12. Disseminate in social media the new gained experience.

F. Assessment – Evaluation

In the following will be discussed aspects on assessment & evaluation only related to "Alpha/Omega Fintech"**.** Similar tasks are planned for any STEAME project.

The formative assessment will ask teachers to check for understanding through classroom discussions, and how teachers will help facilitate discussion and correct misconceptions, if necessary. Moreover, the exit ticket at the end of the lessons will help gauge student understanding. Therefore, the opening discussion will allow teachers to check for understanding of the material as well as the end of class discussion about the results.

A special interest should consider the continuous formative evaluation which involves:

- *Quizzes and Problem-Solving Exercises:* Regular quizzes assessing knowledge of budget management (income, expenses, savings), spending wisely, concept of investing and how it can help grow money over time, expected value, insurance, insurance policy, risk management.
- *Group Presentation Rubrics*: Evaluating group presentations about the concepts of insurance and annuities focusing on accuracy in data representation, depth of analysis, and understanding of this process.
- *Calculation Accuracy Checks*: Assessing the accuracy of calculations made during sessions related to a budget, cost analysis, insurance policy, life insurance policy
- *Peer and Self-Assessment*: Encouraging students to assess their and their peers' work during group activities, fostering a reflective approach on understanding and teamwork.

IV. IMPLEMENTATION IN HYBRID ENVIRONMENTS

A Hybrid Learning Environment (HLE) is a mixture of School-Based Learning (SBL) - where "learning is central" and Work-Based Learning (WBL) - where "working is central", as described in [9][10]. Recently, the term hybrid referred also to face to face and online learning (or ICT-based learning). According to [9], SBL "*can be characterized as intentional, organized in a formal curriculum, with predictable outcomes and with a focus on explicit knowledge and generalized skills*". By contrast, WBL is "*unintentional and informal*" [9] and is promoted in vocational and technical education [10].

STEAME education uses multidisciplinary-based PBL being suitable for HLE. For the STEAME projects described in Section 3, we considered all three ways: SBL, WBL, and online (mobile) learning using Open Educational Resources (OER) depending on L&CP. OER items are offered by schools or online platforms like PhET [11] and STEAME repository [12].

Figure 1. School-based learning.

Figure 2. Open space/ work-place learning.

The L&CP described above were discussed and evaluated for two days training activities in May 2025 for 16 ST and 10 TS (Figure 1) and in October 2025 (25 TS). The evaluation rubric covered competences, project management, project development and project implementation. Four degrees of performance (1 – initial, 2 – developing, 3 – strong, 4 – exemplary) are collected and analyzed to improve L&CP design. The classification was based on labels: *limited* (0-30%), *adequate* (30-60%), *great* (60-80%), and *excellent* (80-100%). The following results were obtained: adequate (3 L&CP), great (5 L&CP).

Figure 2 displays a learning activity in open space / workplace. OER videos were created for all L&CP to explain their structure. OER interactive lessons are under development.

V. CONCLUSION AND FUTURE WORK

This work presented the design of L&CP according to STEAME-PBL approach to foster the development of entrepreneurial attitudes and skills through learning and teaching across the whole curriculum using modern technologies in HLE. The L&CPs have been implemented using SBL, WBL, blended learning, and HLE approaches.

The present work will continue with specific OER development and their registration on STEAME platform [12].

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From Ora et Labora to Lude et Labora

The Digital Charterhouse as a Human-Centric GenAI Framework for NEET Reintegration and Territorial Digital Tourism

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***Abstract*—The rapid diffusion of Generative AI (GenAI) in education demands holistic frameworks that move beyond tool adoption toward ethical, community-grounded ecosystem design. This paper introduces the *Digital Charterhouse*, a framework designed to anchor GenAI within an ethical manifesto and local economic regeneration and its concrete pilot instantiation through the *Lude et Labora* initiative. Lude et Labora targets NEETs (young adults Not in Education, Employment, or Training) across Italian regions, reinterpreting the ancient monastic principle *Ora et Labora* into a contemporary triad of Play–Connect–Work. Building on earlier active-learning experiments in digital tourism education, the framework orchestrates gamified onboarding, AI-assisted mentoring, and real territorial projects to train a new generation of *AI Tourism Designers*. A quantitative comparative analysis scores the Digital Charterhouse 2.53× higher than a standard GenAI course across sustainability, ethics, and economic-impact dimensions, while the Lude et Labora programme targets 500+ NEETs engaged, 80% completion rate, and 60% employment or entrepreneurship placement within six months.**

***Index Terms*—Generative AI; Digital Charterhouse; active learning; NEET reintegration; digital tourism; project-based learning; local economic regeneration; gamification; ethical AI.**

I. Introduction

The integration of Generative AI (GenAI) into educational contexts has sparked a wave of enthusiasm accompanied by equally significant concerns [7]. Most current deployments treat AI as a productivity layer grafted onto existing curricula, leaving unresolved the deeper challenges of knowledge decontextualization, learner deskilling, and weak connections to real socio-economic needs [10].

Two parallel crises sharpen this problem in the Italian context. First, more than 2.5 million young adults aged 15–34 are classified as NEETs, disconnected from both education and the labour market. Second, Italy's rich cultural and territorial heritage remains largely underutilised as a driver of digital entrepreneurship. Traditional tourism training programmes have begun bridging this gap through active learning and business simulation [1], yet they stop short of providing a systemic GenAI-enhanced framework with explicit ethical grounding.

This paper makes the following contributions:

1) We formalize the **Digital Charterhouse model**—a human-centric GenAI ecosystem grounded in an Ethical Manifesto, PBL for local impact, and profession regeneration.
2) We present **Lude et Labora** ("Play and Work") as the living-laboratory pilot of that model, specifically designed for NEET reintegration and the formation of *AI Tourism Designers* across Italian territories.
3) We provide a **quantitative comparative analysis** demonstrating the model's measurable superiority over standard GenAI frameworks.
4) We trace the **pedagogical lineage** from the active-learning Digital Tourism courses [1] to the current GenAI-augmented ecosystem.

The remainder of this paper is structured as follows. Section II reviews the relevant literature across three converging strands: active learning and business simulation in digital tourism education, the current state of GenAI in education, and the emerging intersection of AI with cultural heritage and the future of work. Section III presents the Digital Charterhouse model in full, covering its philosophical foundations (the Ethical Manifesto), its three operational pillars (Ethical AI Tutor, Project-Based Learning for Local Impact, and Regeneration of Professions), and the architecture of its functional web-application platform. Section IV introduces Lude et Labora as the concrete pilot instantiation of the model, detailing the Play–Connect–Work triad, a worked territorial use case (the Olive Oil Journey), and the multi-stakeholder partnership ecosystem spanning the University of Rome "Tor Vergata" and non-profit Territorial Cloisters across Lazio, Abruzzo, and Umbria. Section V provides the multi-dimensional analytical validation of the framework, including sustainability and impact indicator analysis, a mockup platform assessment, a quantitative comparative scoring matrix, and the projected outcome targets for the Lude et Labora pilot. Section VI discusses the principal innovative results, addressing the shift from tool-use to ecosystem design, the NEET-specific innovation of playful reactivation, the ethical and ecological rationale for local LLM deployment, and the explicit pedagogical continuity with prior active-learning work. Finally, Section VII draws conclusions and outlines directions for future empirical research.

II. Background and Related Work

A. Active Learning and Business Simulation in Digital Tourism

Prior work at the University of Rome "Tor Vergata" established a foundational active-learning methodology for Digital Tourism education [1]. That study introduced an Online Travel Agency (OTA) Business Simulation platform based on web-coding laboratories synchronized with the Microsoft Teams collaboration environment. Students acted as digital tour operators, developing real booking portals, destination maps, and multimedia travel stories—culminating in an outdoor Smartourism Hackathon at the Tevere Park. The resulting competency framework (Table I) demonstrated that real-world simulation, rather than abstract tool use, yields measurably richer cognitive, digital, action-oriented, and social learning outcomes [1]. This line of work constitutes the empirical precedent that the Digital Charterhouse model now extends toward GenAI-enhanced, community-focused education.

TABLE I
Learning Outcomes Framework from OTA Business Simulation [1]

Domain	Competencies	Skills
Cognitive	Destination discovery; planning & risk analysis	Digital analytical skills
Digital	Web, map & multimedia design	Creativity; content creation
Action	Self-management of travel business	Independence; self-learning
Social	Tour integration; networking	Communication; team-working

B. GenAI in Education: State of the Art

Systematic reviews confirm GenAI's efficacy in improving student motivation and engagement [14], yet they consistently highlight the absence of long-term, ethically-grounded pedagogical architectures [15]. Reviews in entrepreneurship education explicitly call for frameworks possessing "global characteristics"—sustainability, ethical reasoning, critical thinking, and authentic real-world problems [15]—a gap the Digital Charterhouse is designed to fill.

C. AI, Heritage, and the Future of Work

The intersection of AI and cultural heritage tourism is an emerging research frontier [12], [13]. These studies highlight both the opportunity—AI-enhanced visitor experiences, intelligent itinerary planning, accessible interpretation—and the risk of homogenising local identities through generic, cloud-based content. The Digital Charterhouse addresses this tension by embedding AI within locally curated knowledge bases (Retrieval-Augmented Generation, RAG) that preserve territorial specificity.

III. The Digital Charterhouse Model

A. Conceptual Foundations

The Digital Charterhouse draws its name and ethos from the historical Carthusian monasteries (*Chartreuse*/*Certosa*) of medieval Europe—communities where individual contemplation and communal purpose coexisted. The model reinterprets this heritage as a digital ecosystem where learners, guided by an ethical AI, pursue reflective, project-based inquiry *within and for* their local communities (Figure 1).

B. Ethical Manifesto: The Non-Negotiable Foundation

Three principles constitute the non-negotiable base layer:

- **Human-Centricity**: AI augments human intellect and creativity; it does not substitute it [8].
- **Intellectual Transparency**: AI contributions must be made explicit; learners are guided to critically engage with and cite AI-generated content [9].
- **Ecological & Social Responsibility**: The model privileges low-impact, locally deployed LLMs (e.g., Ollama stack) and targets local social and environmental challenges [11].

C. Operational Pillars

The Ethical AI Tutor functions as a Socratic guide rather than an answer generator. It asks probing questions, draws on a curated local RAG knowledge base, and systematically enforces intellectual transparency. Crucially, it is constrained by—and empowered by—locally curated documents, preventing the generic outputs typical of cloud-based LLMs.

Project-Based Learning for Local Impact defines an emergent curriculum driven by authentic community challenges: revitalising an artisan craft, improving rural tourism, or solving a local environmental issue. This ensures that learning remains both relevant and applied [11].

Regeneration of Professions is the ultimate output of each learning cycle. A traditional baker uses AI for personalised nutrition planning and digital marketing. A local olive-oil producer becomes an AI Tourism Designer. The model thus directly addresses the skills gap by augmenting—rather than displacing— traditional and local economic roles [13].

D. Platform Architecture

A functional web-application mockup embodies the model with four integrated components:

1) **Leaflet Map** ("The Territory"): geographic visualisation of local context—kiln sites, artisan workshops, material sources—grounding abstract learning in mappable reality.
2) **Chatbot** ("The Ethical AI Tutor"): context-aware interface to a local LLM; clicking a map location triggers a RAG query returning historically accurate, site-specific answers.
3) **Digital Library** ("The Curated Knowledge Base"): RAG-enabled repository of historical documents, technical papers, and artisan interviews.

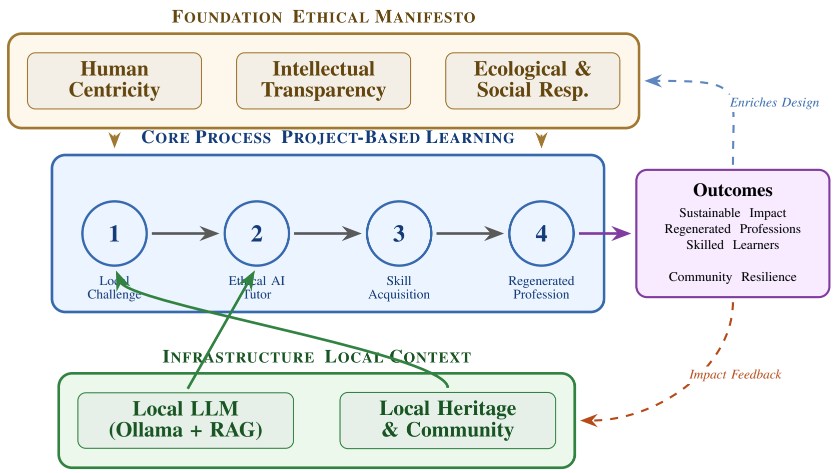

Fig. 1. The Digital Charterhouse Ecosystem: three interdependent layers—Ethical Manifesto (foundation), Project-Based Learning cycle (core process), and Local LLM infrastructure—linked by forward-flow and feedback arrows.

4) **Itinerary Planner** ("The Project Scaffold"): connects map locations, library resources, and chatbot sessions into a coherent PBL pathway.

IV. LUDE ET LABORA: THE PILOT INSTANTIATION

A. *From* Ora et Labora *to* Lude et Labora

The Benedictine principle *Ora et Labora* ("Pray and Work") structured medieval monastic communities around prayer and manual labour. The Digital Charterhouse reinterprets this duality for contemporary digital education, producing the triad *Lude et Labora*: **Play – Connect – Work**. This shift is deliberate: the playful dimension is the key to reaching and retaining NEET populations who have disengaged from traditional educational pathways.

B. The Three Operational Pillars

a) LUDE (Play) — Experiment & Discover: Ludic onboarding via serious games, creative challenges, real-world simulations, and gamified learning pathways. The gaming dimension echoes the outdoor Hackathon experience demonstrated in earlier digital tourism courses [1], now systematised and extended with AI-assisted narrative games.

b) ET (Connect) — Build & Network: Personalised 1-to-1 mentoring relationships, peer learning in collaborative communities (the *Cloister*), and intergenerational knowledge exchange (the *Chapter Hall*). The monastic architecture metaphor is thus operationalised as a digital pedagogy: Cloister (peer collaboration), Chapter Hall (mentoring), Digital Library (AI-enhanced knowledge), Scriptorium (project laboratory).

c) LABORA (Work) — Create & Deliver: Real project work for local territories, DigComp and AI certifications, and professional portfolio development. Outputs are not academic exercises but concrete business or cultural regeneration plans validated by the community.

C. A Concrete Use Case: The Olive Oil Journey

The sequence below illustrates a complete Lude et Labora cycle targeting the regeneration of an olive-oil producing territory:

1) **LUDE**: Participants engage in the narrative game "Oil & History," exploring centuries of local production tradition through gamified discovery.
2) **ET**: Community reflection on local olive-growing heritage; intergenerational knowledge transfer between elderly growers and young participants.
3) **LABORA**: Deliverables include an AI tourist chatbot, an "Open Mills 2.0" digital itinerary, and a promotional event plan.

Transformation outcome: NEET $\rightarrow$ *AI Tourism Designer*—a skilled professional creating territorial value through digital innovation and cultural storytelling.

D. Partnership Ecosystem

The programme operates through a two-tier alliance:

- **The Academy** (University of Rome "Tor Vergata"): Ethical AI Manifesto development, platform infrastructure, gamification methodology, and research validation.
- **Territorial Cloisters** (non-profit associations and municipalities in Lazio, Abruzzo, and Umbria): NEET identification and outreach, local cultural content development, community space activation, and regional network coordination.

V. ANALYTICAL EVALUATION

A. Sustainability & Impact Indicator Analysis

Table II compares the systemic properties of the Digital Charterhouse against a standard GenAI-enhanced course across environmental, socio-educational, and economic dimensions.

TABLE II
COMPARATIVE SUSTAINABILITY & IMPACT INDICATORS

Dim.	KPI	Std. AI	Dig. Charterhouse
Env.	Carbon footprint	High	Reduced (local LLM)
	Data sovereignty	Low	High
Socio-Ed.	Contextual relevance	Low	High (local PBL)
	Ethical thinking	Variable	Embedded
Econ.	Job transformation	Abstract	Concrete & direct
	Cost sustainability	Recurring	Lower long-term

B. Quantitative Comparative Analysis

A weighted scoring model (0–5 per dimension) quantifies the performance differential between the Digital Charterhouse and a traditional GenAI framework, as shown in Table III. Weights reflect the priorities identified in the reviewed literature: contextual and pedagogical depth (15% each); sustainability and ethics (10% each); economic and operational dimensions (10–15%).

TABLE III
QUANTITATIVE COMPARATIVE ANALYSIS MATRIX

Dimension & Metric	W	Trad.	DC	W.T.	W.DC
1. Contextual & Pedagogical Depth					
Relevance of AI Outputs	15%	1	5	0.15	0.75
Critical Thinking Support	15%	2	5	0.30	0.75
Pedagogical Alignment	10%	2	5	0.20	0.50
2. Sustainability & Ethics					
Data Sovereignty	10%	1	5	0.10	0.50
Environmental Impact	10%	2	4	0.20	0.40
Explicit Ethical Framework	10%	1	5	0.10	0.50
3. Economic & Practical Impact					
Job Market Alignment	15%	3	5	0.45	0.75
Operational Cost Efficiency	10%	3	4	0.30	0.40
Tool Integration Cohesion	5%	2	5	0.10	0.25
TOTAL	100%			**1.90**	**4.80**

The Digital Charterhouse achieves a total weighted score of **4.80**, which is **2.53**$\times$ higher than the traditional GenAI score of 1.90. The exploratory scoring model suggests a substantial comparative advantage of the Digital Charterhouse across contextual, ethical, and economic dimensions. However, these results should be interpreted as heuristic rather than conclusive, as the weighting system reflects model-internal assumptions that require validation through longitudinal empirical research

C. Comparative Outcome Analysis: Lude et Labora vs. Traditional Training Platforms

Table IV benchmarks Lude et Labora across five key performance dimensions against three reference categories of established training provision: (i) *Generic e-Learning Platforms* (e.g., Coursera, edX, Google Career Certificates), representing scalable but decontextualised digital training; (ii) *Public NEET Programmes* (e.g., EU-funded Garanzia Giovani / Youth Guarantee schemes operating in Italy), representing institutionally backed, wide-reach initiatives with labour-market integration goals; and (iii) *Sector-Specific Bootcamps* (e.g., intensive coding or digital marketing bootcamps with employer partnerships), representing the current state-of-the-art in accelerated employability training.

1) Completion Rate: The most striking contrast lies in programme completion. Generic MOOCs on platforms such as Coursera and edX have been widely reported to achieve completion rates of only 5–15%, irrespective of content quality, due to the fundamental absence of social accountability and contextual relevance [2]. EU Youth Guarantee schemes in Italy perform considerably better (55–65%), benefiting from structured mentoring and institutional follow-up, but still fall short of the 80% completion target of Lude et Labora. The gamification mechanism—specifically the Serious Game onboarding (LUDE phase) and the community-belonging reinforcement (ET phase)—is hypothesised to be the primary driver of this performance differential. This hypothesis is grounded in the established efficacy of gamification in sustaining learner motivation over time [3], and in the empirical observation from the earlier digital tourism hackathon [1] that outdoor, game-mediated learning produced significantly higher student engagement and self-reported awareness compared to classroom-only equivalents.

2) Employment and Entrepreneurship Placement: A 60% placement rate within six months is conservative relative to the best-performing sector bootcamps (60–70%), yet substantially above both generic e-learning (20–35%) and public NEET programmes (35–45%). The key differentiator is the nature of the placement pathway: bootcamp graduates typically enter a predefined employer pipeline in tech-centric roles, while Lude et Labora graduates are positioned as *AI Tourism Designers*—a hybrid profile for which local demand is not pre-structured but must be partially created through the territorial deliverables themselves. This means the 60% figure encompasses both employment and entrepreneurship (micro-enterprises, freelance digital consultancy, co-operative models), which is a richer and more resilient outcome distribution than the wage-employment-only metrics of bootcamp reports.

3) Territorial Deliverables as Structural Innovation: No existing platform category produces *territorial deliverables* as a primary outcome metric. Generic e-learning platforms produce certificates; bootcamps produce portfolio projects often disconnected from local contexts; Youth Guarantee programmes produce internship placements. Lude et Labora is distinctive in defining 15 *community projects* as a Year-1

TABLE IV
COMPARATIVE OUTCOME ANALYSIS: LUDE ET LABORA VS. TRADITIONAL TRAINING PLATFORMS

Outcome Dimension	**Generic e-Learning** *(Coursera/edX)*	**Public NEET Programmes** *(Youth Guarantee/IT)*	**Sector Bootcamps** *(Digital/Coding)*	**Lude et Labora** *(Digital Charterhouse)*
Completion Rate	5–15% [2]	55–65% [4]	70–80% [5]	**80% (target)** *Gamified PBL + community bonding*
Employment / Entrepreneurship Rate (6 months)	20–35% [6]	35–45% [4]	60–70% [5]	**60% (target)** *Territorial anchoring + real deliverables*
Territorial / Local Deliverables	None *(generic certificates)*	Marginal *(internship placements only)*	None / Generic *(portfolio projects)*	**15 community projects (Year 1)** *Chatbots, itineraries, events*
Contextual / Cultural Grounding	Very low *(global, standardised)*	Low *(sector-generic)*	Low *(tech-centric)*	**Very high** *Local RAG + heritage datasets*
Ethical AI Framework	Absent	Absent	Minimal	**Structurally embedded** *Ethical Manifesto + Tutor*
NEET-Specific Re-engagement	Low *(self-selection bias; drop-out high)*	Moderate *(outreach programmes)*	Low *(entry barriers: fees, skills)*	**High (design priority)** *Gamified onboarding; zero-barrier entry*
Cost per Learner *(indicative)*	$0–50 *(subsidised/freemium)*	800–2 500 [4] *(EU co-funded)*	3 000–8 000 *(market-rate)*	**< 1 500 (est.)** *Local LLM; community infra*

target—outputs that simultaneously serve as learning assessments, local economic contributions, and proof-of-concept for the Digital Charterhouse model's regeneration thesis. This transforms learner outputs from individual credentials into collective territorial assets, aligning with the model's ambition to function as a driver of local economic regeneration rather than merely individual upskilling.

4) Cost-Efficiency and Scalability: The estimated cost per learner of under €1 500 compares favourably against the EU-co-funded Youth Guarantee expenditure of €800–2 500 per participant [4] and is substantially below the market rate for sector bootcamps (€3 000–8 000). This cost structure is enabled primarily by the use of locally deployed open-source LLMs (Ollama stack) in place of commercial API subscriptions, and by the community infrastructure of Territorial Cloister partners, which provides physical and social capital at marginal cost. As the local RAG knowledge base matures across iterations, average cost per learner is expected to decrease further, yielding a favourable long-term cost curve compared to platform subscriptions that scale linearly with learner volume.

5) Summary Assessment: The comparative analysis reveals that Lude et Labora occupies a distinctive position in the training-provision landscape: it matches or approaches the completion and placement rates of the best-performing sector bootcamps while simultaneously delivering on dimensions—contextual grounding, ethical AI integration, territorial impact, and NEET-specific re-engagement—that no existing platform category addresses. The combination of these attributes is not incidental but structurally determined by the Digital Charterhouse model's ecosystem design, confirming that the 2.53× quantitative advantage documented in Table III translates into plausible and differentiated real-world outcomes.

VI. INNOVATIVE RESULTS AND DISCUSSION

A. From Tool-Use to Ecosystem Design

The most significant theoretical contribution of this work is the shift of discourse from *GenAI as a tool* to *GenAI as an ecosystem component*. Earlier active-learning experiments in digital tourism [1] demonstrated that authentic simulation—students building real web travel agencies, exploring real destinations, participating in outdoor hackathons—produces richer and more durable competencies than isolated software exercises. The Digital Charterhouse generalises this insight: the ecosystem *is* the curriculum, and AI is one element within it, constrained and empowered by local knowledge and community purpose.

B. The NEET-Specific Innovation: Playful Reactivation

A fundamental innovation of Lude et Labora is its response to the psychological profile of NEET populations. Disengagement is often not a deficit of capability but a failure of relevance and belonging. The gamified onboarding sequence (LUDE) lowers the barrier to entry; the community dimension (ET) rebuilds trust and social capital; and the real-project work (LABORA) restores a sense of agency and vocation. This arc is substantively different from generic upskilling programmes and from standard GenAI-enhanced courses.

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C. Local LLM as an Ethical and Ecological Choice

The deployment of locally hosted LLMs (Ollama stack with RAG on curated territorial datasets) is not merely a technical choice but an ethical and ecological one. It eliminates cloud-dependency and the associated carbon footprint; it prevents data leakage of sensitive cultural and personal information; and it anchors AI knowledge to the specific heritage of the territory being studied, avoiding the generic, decontextualised outputs that characterise public LLMs. This aligns with emerging policy frameworks on AI and sustainability in higher education [11].

D. Bridging Active Learning and GenAI

The pedagogical lineage of this work is explicit. The OTA Business Simulation [1] established four key principles: (1) autonomous group task definition within a shared scaffold, (2) agile scrum synchronisation, (3) natural output sharing via web platforms, and (4) cross-disciplinary facilitation. The Digital Charterhouse preserves all four, adds the Ethical AI Tutor and local RAG library, and scales from a single course to a multi-regional social programme. The continuity demonstrates that the model is not a speculative proposal but a grounded evolution of a tested pedagogical tradition.

E. Limitations and Future Research

This study presents several limitations.

- First, the university experiment is exploratory and based on qualitative observation without formalized measurement protocols.
- Second, the sample size is limited and not statistically representative.
- Third, the comparative scoring model is internally constructed and does not constitute an externally validated evaluation framework.
- Finally, the comparison with existing training platforms is indicative and not based on controlled experimental conditions.

These limitations define the current contribution as a preliminary investigation rather than a conclusive validation.

VII. Conclusion

This paper has presented the Digital Charterhouse model and its pilot instantiation as Lude et Labora, tracing a coherent lineage from foundational active-learning experiments in digital tourism [1] to a GenAI-augmented, community-rooted, ethically grounded educational ecosystem. The model achieves a quantitative performance score 2.53$\times$ higher than standard GenAI frameworks on the dimensions that matter most: contextual pedagogical depth, sustainability, and tangible economic impact.

The Digital Charterhouse does not provide a definitive model, but proposes a structured approach to rethinking the relationship between space, community, and technology in education.

The preliminary experimental results suggest that such an approach may be particularly effective in intercultural and practice-based learning environments.

Future work will be required to validate these findings through longitudinal and comparative studies.

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Navigating Memory Palaces: The Role of Instructional Agents in Teaching the Method of Loci in Virtual Reality

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***Abstract*—With mnemonic techniques like the Method of Loci, learners are able to recall vast amounts of content reliably and for a long period of time. Students, however, often have little knowledge of such helpful techniques. Teaching the Method of Loci is challenging as it is based on mental imagery. The combination of Virtual Reality (VR) and virtual agents offers a solution for this, as the memorization method can be explained visually by the agent. To investigate the effects of this solution, we created a VR application where learners first design a series of virtual rooms and then place representations of memory objects into them with the agent's help. Secondly, they engage in recall through guided inspection, with the agent leading from location to location. We evaluated this approach in a comparative user study with 27 participants. Quantitative results show that learners who are introduced to the Method of Loci with the VR agent application initially show similar memory performance as students learning in traditional ways, but remember significantly better in a follow-up test one week later. Qualitative results indicate that with VR agents, students can practice the Method of Loci effectively. In the follow-up test, they were able to transfer it to new memorization tasks, where they performed more accurately, quickly, and confidently than their peers, even when not relying on the VR visualization. This highlights that VR and virtual agents can help teach mnemonic techniques to students. The results contribute towards the design of learning paths where students are first introduced to enjoyable learning methods by VR agents before being able to apply them efficiently.**

Keywords-Virtual Reality; Intelligent Tutoring Systems; Virtual Agents; Mnemonics; Method of Loci.

I. INTRODUCTION

Remembering and memorizing information is an important element of learning. Memorization clears up space in the limited working memory by moving information to the long-term memory [1]. This reduces the cognitive load and allows for complex thinking [2][3], improving task performance [4].

Despite this, many students apply ineffective learning methods [5] and are unfamiliar with mnemonic techniques that can improve their long-term retention [6]. One such mnemonic technique is the Method of Loci (MoL), which was already used in ancient Greece to memorize speeches and is still used today, e.g., by memory athletes [7]. The technique utilizes the brain's ability to create a mental map of our surroundings to remember and locate points of interest [7][8]: The student thinks of a familiar place, sometimes called a memory palace — their apartment, the classroom, or the path to university — and traverses it along a fixed route. On this path, the learner selects significant locations, e.g., on a desk, at an entry door or next to a lamp. Next, the learner imagines objects in these locations which represent the information to be memorized. To recall the information, the student can imagine walking the route again. At the specific spots, the placed mental images are recalled along with the associated pieces of knowledge.

Learners usually apply the MoL fully in their imagination without producing any tangible visualizations. This makes it challenging for educators to convey the method to students and to check whether they apply the method correctly. Here, Virtual Reality (VR) offers large potential by visualizing the imaginary parts of the MoL [9]. The learner can create and populate an arbitrarily large number of virtual environments with information. These rooms and the represented information can stay persistent, allowing the student to revisit them and to invite others to inspect their memory palace.

Moreover, guiding the student through the memory palace and the creation process has a positive effect on accepting the mnemonic technique [10]. A scalable way for such guides are virtual agents as simulated instructors [11]. The combination of the MoL with guidance of virtual agents is not well researched yet. Hence, the goal of this study is to research how VR and virtual agents influence students' ability to understand and apply the MoL. Our contributions in this paper are:

- A concept for integrating VR agents to guide learners in creating and using memory palaces in the MoL.
- A design and implementation of an open-source VR application to realize VR agents teaching the MoL.
- A user study about the learning effect, motivation and learning experience with VR agents conveying the MoL.

The remainder of the paper is structured as follows: In Section II, related research about the MoL in VR and instructional agents is presented. Section III describes our implemented VR system which users can utilize to build virtual memory palaces. In Section IV, this application is evaluated with users in a comparative study. Section V concludes the paper with a summary of central results and an outlook.

II. Related Work

Our study combines the mnemonic technique of the MoL with guidance by VR agents. We included studies with a user evaluation of the MoL in digital settings with a focus on VR systems. Moreover, we looked for studies about VR agents which were used as guides to cover both topics. The literature showed no studies combining the MoL and VR agents.

A. Method of Loci in Virtual Reality

Several studies investigated how to transfer the MoL to VR and digital worlds. For instance, Reggente et al. [12] applied the MoL to a desktop-based virtual environment. Their study compared users who are learning a list by freely placing 3D objects in the virtual world with those who could only observe the items in a static location. Learners who could place content freely in the environment were quicker and more accurate in recalling the list in forward and reverse order. This shows that humans' spatial memory also works with virtual worlds after learners have familiarized themselves with the environment.

Going beyond 2D screens, Huttner and Robra-Bissantz [13] and Krokos et al. [14] reported improved recall accuracy with the MoL in VR and increased immersion compared to desktop experiences. Participants were also significantly more willing to apply the MoL in VR [13] and reported higher spatial awareness, even though they were previously unfamiliar with VR Head-Mounted Displays (HMDs) [14].

Similar results were also presented by Moll and Sykes [9], who compared traditional learning methods with a VR-based MoL. The VR system led to significant improvements of 20.4% and 22.2% in recall compared with traditional learning methods in the two repetitions of the experiment, respectively. Moreover, the authors observed that participants acquired varying understandings of the MoL after a brief textual explanation. This led to differences in applying the MoL and influenced the recall success, underlining the need for a guided visual introduction to this mnemonic technique.

B. Virtual Agents as Guides

The literature also examines how virtual agents can mimic human guides and help in training scenarios. For instance, Hammady et al. [15] apply them as a MR museum guide. By utilizing storytelling, visualizations and audio narration, the agent leads the user through a series of waypoints while explaining the exhibitions. Because of the agents, users enjoyed the experience more and stayed longer in the museum.

The simulation of humans by virtual agents was also investigated by Bickmore et al. [16] in a presentation training application. In their study, the agent acts as a co-presenter so that the user can practice public speaking. Rated presentation recordings show that users significantly improved the quality of their presentations with the support of the agent. Moreover, non-native English speakers increased their confidence.

A common denominator of these studies is the high user satisfaction with the interaction with agents and the agent's ability to support the task performance. This is also supported by our previous studies where agents demonstrate assembly tasks [11] and visualize actions for accessible language learning [17]. Interactions with the agents were intuitive to users, leading to a high usability score of the applications. In the language learning use case, the performance was comparable to traditional vocabulary learning, but the agents caused a higher engagement and enjoyment [17].

These results highlight that VR agents can turn learning tasks into motivating experiences. This makes them a promising tool for conveying the MoL to learners.

III. Realization

In order to gain insights about the MoL with virtual agents, we implemented an open-source application (https://github.com/rwth-acis/MR-MiRA-Method-of-Loci-App) for the Meta Quest 2 and 3. The system allows users to set up a virtual environment in VR and fill it with elements for memorization. A virtual agent advises how to use the MoL and guides through the created memory palace.

A. Used Technologies

We developed the system using the Unity 3D engine and the Meta Software Development Kit (SDK). The simulated guides are created with our virtual agents framework [11]. With this resource, we can quickly integrate virtual agents into a project according to our reusable toolkit structure [18]. Developers can define the agent's behavior by sending tasks to the agent. We adjusted the visual appearance of the agent by loading a model from the ReadyPlayerMe service. Objects in the environment are prepared and modeled with the 3D software Blender.

B. Learning Workflow

Users progress through several stages: the setup phase, the memory forming phase and the guided repetition phase.

1) Setup Phase: During the setup phase, the learner constructs the virtual rooms. The overall shape of each room reflects the dimensions of the user's real room using the spatial map of the Meta Quest 2 and 3. The HMD's virtual boundary system also highlights real-world obstacles. Thus, the user can comfortably explore the space and grasp its spatial layout.

The user can select furniture objects in a menu and place them in the environment to personalize the space and to form an intuitive understanding of the room's structure. The furniture can either be placed using the Meta Quest's controllers or by direct hand tracking. To visualize the touch interactions of the hand, the system streams the HMD's camera feed, extracts the user's real hands from it, and displays them in VR.

During the setup of the room, the virtual agent follows the user. Upon first use, the agent teaches about the possible interactions, how to find furniture objects, and how to place them. It also encourages the user to place a sufficient amount of objects and to create multiple rooms so that enough content can later be memorized in the space.

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After setting up one room, the user can create and furnish further rooms. Within one virtual memory palace, the created rooms are automatically connected via color-coded doors. Purple doors indicate that the learner progresses further into the memory palace, whereas green doors lead back to previous rooms. The user can teleport to the connected room by touching the doors. This creates a sequence of rooms where each one can be individualized and look distinct. Through this setup, the user is nudged to create a linear route for the memory forming process, as recommended for the MoL.

2) Memory Forming Phase: After furnishing the rooms, the memory forming phase starts. Here, users can place 3D objects in the room to represent pieces of information to memorize. We will refer to these 3D objects for the remainder of the text as *information objects*. These information objects can be selected from a list of 103 objects, categorized into animals, people, cars, food and more. Hence, the user can choose freely how to visually encode the items to memorize them. To further enhance the memorability of the information objects, some of them have sounds attached to them like the siren of an ambulance, making the learning experience multimodal.

The information objects have a different visual style to distinguish them from the furniture, as depicted in Figure 1. Whereas the furniture has wooden textures, the information objects have a colorful low-poly style to catch the learner's attention. An optional mode grays out all room-related furniture, so that all information objects are highlighted at a glance.

Figure 1. An example of a room in a memory palace. Information objects are placed on the furniture.

The virtual agent advises on the process of the MoL while the user populates the room with information objects. It suggests suitable 3D objects to represent the pieces of knowledge. Moreover, it monitors the number of information objects in the space, warning the user to proceed to another room if the space becomes overloaded with information. Once all information objects are placed, the agent guides the user through the entire memory palace to establish a fixed route.

3) Guided Repetition Phase: This guidance activity leads to the guided repetition phase. The user and the agent start at the first placed information object. Then, sequentially, the agent walks to the next information object and points at it as depicted in Figure 2. A spotlight above the object is activated to draw attention to it. Once the user confirms the step, the agent proceeds to the next station in the route. The tour can be repeated multiple times to manifest the memory of it. This

Figure 2. A screenshot from the application, showing the agent pointing at an information object represented by a pine tree.

setup enables a spaced repetition approach. Learners can revisit the memory palace at any time since the application saves the spatial configuration of the furniture and the information objects. Spatial anchors ensure that the placed content remains at exactly the same physical locations since the virtual room's dimensions relate to the real room. The positional data are stored as a JavaScript Object Notation (JSON) file and can, therefore, also be shared with other learners.

IV. Evaluation

The implemented application was evaluated to assess the resulting understanding of the MoL by measuring: recall, usability, motivation, ability to apply the MoL, time efficiency, and application performance based on the number of objects.

A. Setup

Using a between-subjects design, the VR group, who used the Meta Quest 2 or 3, was compared to a control group that learned without technical support. The learning materials consisted of a list of 15 objects, a short story and a 20-digit number. Figure 3 depicts an overview of the study's procedure. Participants in the VR group received an introduction to the MoL, designed six to ten rooms with furniture and were given 40 minutes to learn the provided information, by placing information objects along a chosen path through the rooms. At each step, the agent supported the users and explained the procedure. After placing the information along the path, the agent helped revisit the rooms in the correct order of the loci. The control group was allowed to learn with their own methods, and had to describe them afterwards.

After the learning sessions, the participants were asked to answer several questionnaires: A knowledge test where they had to recall the list, answer 16 questions regarding the story, and state the learned number. They also answered 30 questions of the Intrinsic Motivation Inventory (IMI) [19]. The VR group additionally rated the application on the System Usability Scale (SUS) [20]. To assess the long-term memory performance, participants answered a follow-up test one week later. It consisted of the same recall tasks and four new questions. To test the understanding and transfer capabilities of the MoL, the VR group was tasked to learn another list of 20 words, using the MoL without VR support. The control group had to learn the list with the same method as in the prior week. Both groups had ten minutes of learning time.

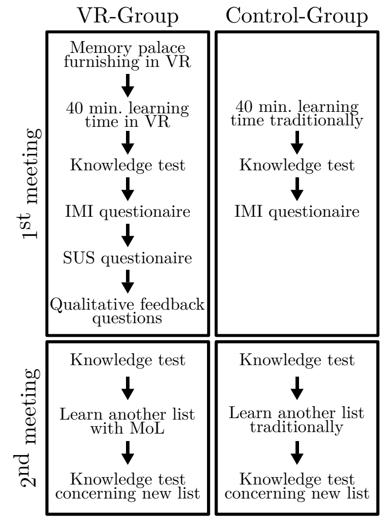

Figure 3. A graphic visualization of tasks and questionnaires of the evaluation.

B. Demographics

In total, 27 participants took part in the evaluation. 14 persons were in the VR group. Three of these participants were excluded in the analysis of the knowledge tests since one had difficulties with the teleportation and did not use the application till the end, one did not interact with the application, and one had difficulties in understanding the language. 13 participants formed the control group where one person did not take the second knowledge test.

1) Virtual Reality Group: The VR group consisted of nine women, three men, and two other genders, between the ages of 20-58 years, with an age average of 27.4 years. Ten of the participants were students, three employees, one was an apprentice. Seven persons had a background in computer science. Participants rated their VR knowledge with 2 out of 5; four people had used a VR HMD before. They rated their previous knowledge of the MoL on average with 1.6 out of 5; only one person had applied it before. Participants assessed their frequency to memorize during learning with an average of 2.9 out of five. They deem such memorization activities reasonable with an average of 3.4 out of five. Moreover, they rated their subjective concentration levels during the study with an average of 3.4 on a five-point Likert scale.

2) Control Group: Eight women and five men were part of the control group, aged between 20 and 62 years with an average of 32.2 years. Seven of the control group were students, four working, one an apprentice and one retired. They rated their required memorization frequency with 2.5, the memorization reasonability with 3 and the subjective concentration levels with 3.

C. Results

We collected results about the retention success and the learning efficiency. We analyzed the system's usability and the user feedback. To study the impact of the instructional agent, we measured the degree to which learners applied the MoL after using the system, as well as their motivation.

1) Knowledge Tests: The knowledge test checks the recall of the list, the story and the 20-digit number. To grade the list answers, the sum of differences between the recalled position and the actual position is added as negative penalty points. A wrong or missing word resulted in -5 penalty points. The VR group was slightly better than the control group with 93% of the maximum points compared to 90.6%, as shown in Table I. For the story questions, each correct answer resulted in one point and missing details in 0.5 points. The VR group recalled slightly more content from the story. We graded the number in the same way as the list. The VR group reached 84.3% of points compared to 85.6% in the control group.

TABLE I. RESULTS OF THE KNOWLEDGE TESTS ABOUT THE LIST, STORY, AND NUMBER FOR BOTH MEETINGS.

	Factor	VR	Control
1st Meeting	Points List	-5.286	-7.077
	Performance List	93%	90.6%
	Points Story	14.2	14
	Performance Story	88.6%	87.5%
	Points Number	-15.8	-14.4
	Performance Number	84.3%	85.6%
2nd Meeting	Average List	-17.1	-11.6
	Performance List	82.9%	88.4%
	Points Story	16.1	14.7
	Performance Story	80.5%	73.3%
	Points Number	-28.4	-28.1
	Performance Number	71.6%	71.9%

In the second knowledge test, the VR group recalled 82.9% of the list, and the control group 88.4%. For the story, the VR group recalled 7.1 percentage points more than the control group. In the four new questions, the VR group answered on average 75% correctly, while the control group only remembered 56.3%. The VR group was also better at remembering the order and items of the list. For the number, both groups were almost even with 71.6% in VR compared to 71.9%. In the story, 89.4% stayed the same as opposed to 78.1% for the control group. For the list and numbers, the control group's answers altered less than the VR group's answers.

The VR group was significantly better in remembering the new list at the second meeting than the control group according to a Mann-Whitney-U-Test with $U = 40$ and $p = 0.022$. Only two VR participants made errors, leading to a performance of 99.7% compared to 85.4% in the control group.

2) Time Efficiency: The answer times to questions on the knowledge test were tracked. In the first meeting, the VR group took 6 minutes 56 seconds, and the control group took 6 minutes 53 seconds. In the second meeting, the VR group was 1 minute 30 seconds faster than the control group with 6 minutes 28 seconds compared to 7 minutes 58 seconds. This time difference stems from the story and number questions. For learning the new list in the second meeting, the VR group took on average 6.4 minutes and the control group 9.9 minutes.

Thus, the VR group was faster and had better retention results when applying the MoL.

3) System Usability Scale: The usability of the application was evaluated with the SUS [20]. The system reached an overall score of 73.6, which is considered good [21]. Table II lists the individual averages for the ten SUS statements. In the table, the scale of the evenly numbered, negatively formulated statements is inverted so that a higher score always corresponds to a better performance.

TABLE II. NORMALIZED RESULTS OF THE SUS.

No.	SUS Statement	Avg. Score
1	Intended usage frequency	3.7
2	Low complexity	4.1
3	Ease of use	3.8
4	Independent technical usage	3.5
5	Integration of functions	4.3
6	Consistency	4.3
7	Learning speed	4.1
8	Convenience	4.4
9	Confidence	3.5
10	Immediate use	3.7

4) Motivation: 12 participants indicated a higher motivation for learning with VR. Of the other two, one experienced cybersickness and one based the decision on the kind of learned information. The detailed results are listed in Table III.

TABLE III. RESULTS OF THE IMI.

Subscale	VR	Control
Interest/Enjoyment	5.8	5.1
Perceived Competence	4.5	4
Effort/Importance	5.3	5.4
Pressure/Tension	3.2	3.4
Value/Usefulness	5.7	4.9

5) Qualitative Feedback Questions: The participants of the VR group were asked additional qualitative questions about the perceived performance scalability, perceived efficiency, and usability. Ten participants noticed no performance impact with a large number of rooms. Four persons mentioned that the app seemed somehow slower, and one of them felt the loading times impacted the learning experience. Eight participants thought the learning efficiency to be higher with VR, three without, and two similar between both options.

Eight users praised the intuitive controls. Users also commented positively about the menu staying in the field of view, the hand controls, the background sound, and the alignment of the rooms with the real world. The menu position was also critiqued twice, along with the weight of the HMD.

6) Application of the Method of Loci: 11 participants stated they remember the created rooms at least partially and can apply their MoL route in them. Ten learners think they can reuse the palace for new information, and the remaining four are worried they might confuse information. When asked about their preferred memory palaces, users mentioned their own flat, familiar routes, and an endless hallway. All participants gave a correct description of their MoL usage for learning the list at the second meeting. Furthermore, six applied additional cues like connecting elements to a story or existing objects.

The selection of information objects was helpful to nine participants, and two would like additional recommendations. 11 participants liked the help of the agent; two thought it was not necessary. Furthermore, 11 participants praised the sounds of the information objects, as well as the spoken instructions, while three would prefer additional written text, and one person found the sound distracting.

V. CONCLUSION AND FUTURE WORK

Many students are unfamiliar with memorization techniques like the Method of Loci. Since this technique is fully imaginary, conveying it to students requires a visualization of the memory palace and instructions on how to learn with it. This paper addresses this challenge by studying the impact of learning the MoL in VR with a virtual agent.

We implemented a VR application to visualize the memory palace and lead the learner through three phases: Initially, the learner sets up a virtual environment and furnishes it to become familiar with the rooms. Then, in a memory forming phase, the learner selects differently styled 3D models and places them in the virtual environment to represent information. Finally, the learner traverses the rooms again in a fixed route to strengthen the memories of the placed information objects and their associated facts. Throughout all three phases, a virtual agent assists the learner by explaining the placement controls, by instructing how to apply the MoL effectively and by guiding the learner through the rooms on a fixed route.

We evaluated the VR application in a user study with 27 participants. The study introduced participants to the MoL and compared learning with the MoL against familiar learning methods of a control group. After initially similar performance in the first test, the VR group significantly improved their recall results and answering time compared to the control group in a second test one week after the first. The VR group remembered more content from a story and were better at memorizing new content, even without relying on the VR application. This indicates that the VR application effectively introduces learners to the MoL, particularly if content is presented in a story form. Participants were also more confident at the second test in applying the MoL to new content without the VR aid. The VR group also showed higher interest and enjoyment in the memorization tasks, perceived themselves as more competent, felt less pressure, and attributed higher value and usefulness to memorization. Hence, learners experienced the learning process more positively with the VR application and after being introduced to the MoL. Overall, the combination of a VR memory palace and an explanatory agent leads to a higher performance and motivation.

The study focused on the overall learning effect of the MoL in VR with virtual agents. Future work could investigate the influence of the three phases of setup, memory formation and repetition individually: In the setup phase, it could be studied how the learning effect differs between the customized spaces of our application and pre-made environments. Here, different strategies to familiarize the user with the space could be explored, utilizing the agent. In the memory forming phase, a central question is how expressive the visualization tool needs to be. The list of pre-curated objects could be compared with more flexible Artificial Intelligence (AI)-generated images or 3D models. Thus, the agent can provide further creative input using an Large Language Model (LLM). Future work could aim to quantify the effect of AI support on memorability. Similarly, the repetition phase could utilize LLMs to generate a memorable route autonomously that the agent can then present to the learner. Future work could also repeat the study with a larger sample size to increase the statistical robustness.

All in all, the study demonstrated an effective concept for integrating virtual agents into a VR learning application to convey the MoL. With explanations by the agent, learners became familiar with the memory technique. This effect becomes evident as learners increased their retention abilities and recall speed in memorization tasks after using the VR application. These results are promising as they contribute towards a scalable, individualized digital solution which introduces students to more efficient and enjoyable learning methods.

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