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Evaluating Heutagogy-Based Learning Contracts for Self-Determined Learning in Postgraduate AI Education

Ratandi Ahmad Fauzan[1*], Muharman Lubis[1], Hanif Fakhrurroja[1], Egi Al Fansyah[1], Daffa Shidqi Thamrin[1], Muhammad Rizq Dzaki Asyam[1]
[1]Telkom University, Bandung, Indonesia
**Corresponding Author: ratandiahmadfauzan@student.telkomuniversity.ac.id*

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ABSTRACT

This study evaluated a heutagogy-informed, AI-assisted Learning Contract in a postgraduate Artificial Intelligence course without changing the existing syllabus or Course Learning Outcomes (CLOs). A naturalistic qualitative document analysis examined 28 final Learning Contracts, course records, learning artifacts, and grades using consistent descriptive coding across five CLO-oriented learning segments over one semester. Twenty-seven contracts covered all five CLOs, and all 28 documented resource exploration; however, only three explicitly defined individual learning paths. AI primarily served as a pedagogical assistant (13 contracts), while reflective-ethical support appeared in five. Applied topics showed greater documented depth than ethics and sustainability. The mean final grade was 79.40, interpreted descriptively rather than as evidence of causal impact. Findings indicate that the Learning Contract linked academic requirements, student planning, and learning evidence, supporting resource autonomy and evaluation accountability more consistently than explicit pathway autonomy or AI-use reflection. The approach may inform future CLO-based learning analytics and responsible AI documentation.

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1. INTRODUCTION

Generative artificial intelligence (GenAI) has shifted discussions in higher education from technology adoption toward the design of learning activities, assessment, academic integrity, and responsible human–AI interaction. This shift is particularly relevant in postgraduate Artificial Intelligence (AI) education, where models, tools, and applications evolve rapidly. However, the semester learning plan (Rencana Pembelajaran Semester, RPS) and Course Learning Outcomes (CLOs) remain essential academic references. The challenge is therefore not to replace the existing curriculum, but to allow students to explore emerging AI knowledge while maintaining alignment with expected outcomes and accountable assessment practices [1], [2], [3].

Postgraduate students may differ in their ability to define learning priorities, select reliable resources, critically examine AI-generated outputs, and produce defensible learning evidence. A uniform course structure does not necessarily make these individual decisions visible, while unrestricted flexibility may disconnect learning activities from formal CLOs. This creates a need for a complementary mechanism that balances learner autonomy and academic accountability. In the course examined here, the existing RPS, five CLOs, Lecture and Brainstorming activities, and assessment structure were retained; an AI-assisted Learning Contract was introduced to help students articulate individualized learning plans within those boundaries.

Prior research has examined GenAI governance and assessment in higher education [1], [3], [4], AI-supported self-directed or self-regulated learning [5], [6], the use of learning contracts and agreements [7], [8], [9], and heutagogy in supporting learner agency [10], [11]. These strands provide relevant foundations but do not fully explain their integration in a single, course-level mechanism. The conceptual gap concerns how learner agency, human oversight, and CLO alignment are coordinated; the design gap concerns the availability of a practicable approach that complements existing teaching without requiring a new curriculum or application; and the empirical gap concerns evaluations that connect individual Learning Contracts with course standards, learning artifacts, and achievement records in postgraduate AI education. This study addresses their intersection rather than claiming that learning contracts or AI-supported learning are new in themselves.

The contribution of this study is to evaluate the Learning Contract as both a pedagogical artifact and a structured information artifact. Pedagogically, the contract makes students' goals, resource choices, strategies, intended artifacts, and assessment expectations explicit. From an Information Systems perspective, it makes those decisions available for comparison with CLOs and observable learning evidence through a socio-technical configuration of people (students and lecturers), process (planning, learning, and evaluation), and technology (AI support). Such structured information could inform future educational information systems and learning analytics, although no digital contract-

builder, monitoring dashboard, or recommendation engine was implemented in the present study [12], [13].

The research evaluates a heutagogy-based Learning Contract intervention in one postgraduate AI course involving 28 students. Its evaluation compares the existing RPS/CLO baseline, individual Learning Contracts, and available assignments, projects, and achievement records across five CLO-oriented learning segments. The study interprets patterns of alignment, content depth, AI roles, learning artifacts, and evaluation accountability without treating assessment scores as causal proof of effectiveness. Two research questions guide the analysis: (1) How is the heutagogy-based Learning Contract intervention characterized in a postgraduate Artificial Intelligence course? (2) To what extent does the intervention support students' self-determined learning based on learning processes, artifacts, and achievement data?

1.1. Learning Contract in Higher Education

A Learning Contract translates course-level requirements into explicit decisions about learning goals, topics, strategies, resources, expected artifacts, and evaluation. Earlier scholarship describes its role in individualizing and structuring learning, while subsequent studies discuss accountability and learning agreements, including the responsible use of GenAI in university courses [7], [8], [9]. In this study, the Learning Contract is an individual, course-specific planning and evaluation artifact rather than a general development plan or a stand-alone AI-use agreement. Its distinctive function is to connect students' selected learning paths to the existing CLOs, enabling comparison between what was planned and what can be observed in learning evidence.

1.2. Heutagogy and Self-Determined Learning

Heutagogy emphasizes the learner's capacity to determine learning directions, explore resources, develop capability, and reflect on decisions [10], [14]. In postgraduate education, these principles are relevant because students must address complex problems and justify their academic choices; nevertheless, autonomy benefits from an enabling structure rather than the absence of guidance [11], [15]. Accordingly, heutagogy informs the design of the Learning Contract, while self-determined learning provides an interpretive outcome. The study examines observable indications of agency, resource exploration, learning depth, ownership, and evaluation accountability in contracts and learning artifacts. It does not claim to measure changes in students' psychological self-determination through a longitudinal psychometric instrument.

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1.3. AI-Supported Learning and Responsible Use

GenAI can assist students with explanation, brainstorming, source exploration, feedback, and technical experimentation, but these functions do not automatically produce responsible or self-determined learning [5], [6], [16]. In the AI-assisted Learning Contract, technology is therefore positioned as support for planning and inquiry, not as an autonomous decision-maker. Students remain responsible for selecting and validating resources, justifying learning choices, and accounting for AI contributions, while lecturers facilitate and oversee alignment with academic requirements. The study also examines the roles assigned to AI in students' contracts, distinguishing basic tool assistance from pedagogical, technical, and reflective-ethical support.

1.4. CLO-Based Sprint as an Evaluative Frame

The intervention was evaluated through five CLO-oriented learning segments, termed sprints in this article. Each segment linked an existing CLO with relevant course activities, artifacts, and assessment evidence; the term does not imply a repeated classroom action research cycle or a replacement of the existing teaching method. The RPS supplied the formal baseline, individual Learning Contracts represented planned learning decisions, and quizzes, assignments, projects, and scores provided evidence of realization. Comparing these three layers allowed the study to examine whether students' exploration remained academically aligned and whether their intended learning could be traced to available artifacts. This alignment-and-traceability perspective also provides a basis for interpreting Learning Contracts as educational information artifacts.

2. RESEARCH METHOD

2.1. Research Design

This article reports a qualitative, document-based evaluation of a heutagogy-informed AI-assisted Learning Contract method implemented in a postgraduate Artificial Intelligence (AI) course. The method was designed as a complementary learning mechanism: students articulated goals, learning strategies, sources, intended artifacts, and evaluation plans while the existing semester learning plan (RPS), Course Learning Outcomes (CLOs), teaching activities, and assessment structure remained in place. Consistent with a People–Process–Technology perspective, students retained ownership of learning decisions, lecturers provided academic facilitation and oversight, and generative AI served as supporting technology. The evaluation focused on observable planning and realization evidence rather than testing causal effectiveness or validating an AI model.

The evaluation compared three connected layers: (i) the RPS/CLO baseline; (ii) each student's final Learning Contract; and (iii) available learning artifacts, assessment

submissions, and scores. Five CLO-oriented learning segments, termed sprints, organized this comparison across one semester. Here, a sprint denotes an analytical link between a CLO, learning activity, artifact, and assessment; it does not represent a repeated classroom action research cycle. Figure 1 summarizes the evaluation logic.

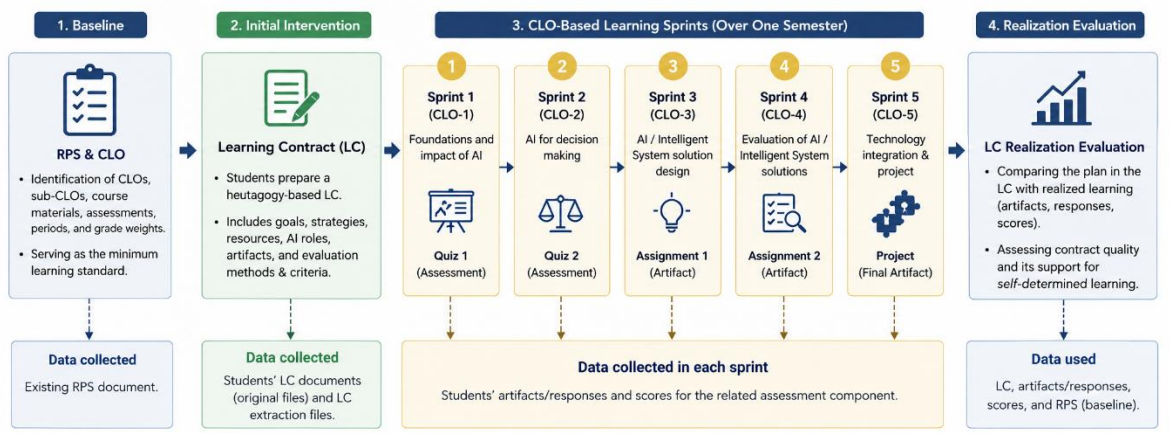


Figure 1. Evaluation design linking the RPS/CLO baseline, Learning Contracts, and learning evidence.

2.2. Research Context and Participants

The study involved one postgraduate AI class in a Master of Information Systems program and 28 students, anonymized as M001–M028. The unit of analysis was each student's final Learning Contract, read alongside its relevant course-level and student-level evidence. All 28 contracts were included in the document analysis. The existing RPS specified five CLOs and five assessment components: Quiz 1, Quiz 2, Assignment 1, Assignment 2, and Project. This was a naturalistic classroom implementation, not a randomized or controlled intervention. The available records support analysis of documented learning intentions, submitted work, and achievement patterns, but not a reconstruction of every decision or interaction that occurred while students used AI.

2.3. CLO-Based Learning Sprint Intervention

The complementary Learning Contract was used within the existing Lecture and Brainstorming learning arrangements. For evaluation, the five CLOs were mapped to course activities and established assessment evidence, as outlined in Table 1. The learning segments provide a common unit for comparing course expectations with student-generated plans and available artifacts; they should not be interpreted as five experimental treatments or successive redesign cycles.

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Table 1. CLO-based learning sprint intervention.

Sprint	CLO	Artifact/Activity	Assessment	Evaluative Function
Sprint 1	CLO-1	Journal review	Quiz 1	Evaluates initial understanding of AI concepts, impacts, and issues in information systems.
Sprint 2	CLO-2	Book-material quiz and class recording	Quiz 2	Evaluates understanding of AI for decision-making in an information systems context.
Sprint 3	CLO-3	Identifying weaknesses of AI output	Assignment 1	Evaluates analytical ability to assess AI-generated output and solution quality.
Sprint 4	CLO-4	AI application and presentation	Assignment 2	Evaluates ability to present and assess AI solutions based on effectiveness and efficiency.
Sprint 5	CLO-5	Project or publication-oriented artifact	Project	Evaluates integration of technology capability, documentation, and final artifact accountability.

2.4. Data Sources and Data Collection

Data were gathered from existing academic documents and available student learning records. The RPS was used to identify CLOs, sub-CLOs, materials, assessment forms, periods, and weights. The final individual Learning Contracts recorded students' selected topics, depth, strategies, resources, lecturer and AI roles, anticipated artifacts, and evaluation approaches. Available quizzes, assignments, project products, and score records were then examined as evidence of realization. Table 2 summarizes the function of each source.

Table 2. Data sources and analytical functions.

Data Source	Form of Data	Function in the Evaluation
Previous syllabus/RPS	CLO, sub-CLO, materials, assessment forms, periods, and weights	Baseline for comparing Learning Contracts and maintaining course alignment.
Students' Learning Contracts	Goals, strategies, resources, instructor role, AI role, evaluation methods, criteria, rubrics, and artifacts	Main intervention data for reading learner agency and contract design quality.
Student artifacts/answers	Quiz answers, assignments, project reports, prototype/code/notebook, or publication-oriented evidence	Evidence for comparing planned learning with realized learning.
Student scores	Quiz 1, Quiz 2, Assignment 1, Assignment 2, Project, and final weighted score	Supporting data to interpret achievement patterns after the intervention.

The analysis used the final versions of the Learning Contracts and available course evidence. It did not include complete AI prompt histories, earlier contract drafts, revision logs, or continuous learning-platform traces. Consequently, the contracts were interpreted

as documented decisions, not as a complete record of students' reasoning or actual AI contributions.

2.5. Analytical Instruments and Evaluation Criteria

Four linked analytical matrices structured the evaluation. First, the RPS/CLO baseline matrix documented formal outcomes, materials, assessment components, periods, and weights. Second, a common Learning Contract extraction sheet captured student identifiers, CLO references, topic coverage and depth, selected sources and strategies, lecturer and AI roles, evaluation methods, criteria, rubrics, and anticipated artifacts. Third, a traceability matrix connected CLO requirements to the corresponding contract plan, observable learning artifact or assessment, and associated result. Fourth, an evaluative synthesis matrix used document-based indicators of learner agency, resource exploration, personal learning pathways, capability, ownership, and evaluability to interpret support for self-determined learning.

Comparisons with the RPS considered whether contract content was reduced, aligned, or extended relative to the formal course baseline. Such judgments were descriptive and depended on relevance to the CLO and the evidence available, not merely on the number of topics or sources listed. Scores were retained as supporting indicators of learning achievement rather than converted into a measure of self-determined learning.

2.6. Data Extraction and Coding Procedure

The coding scheme combined a priori categories derived from the RPS/CLO structure, the Learning Contract components, the study's design requirements, and heutagogical concepts with descriptive examination of the available documents. It served as an operational classification framework rather than a newly standardized psychometric instrument. The academic supervisor conducted the coding of the 28 final Learning Contracts using a common extraction sheet and the same operational category definitions. Original document content was retained as the basis for each classification. The coding categories and their descriptive labels are presented in Section 3.2.

Extraction proceeded in four steps. First, formal CLOs and relevant materials were identified from the RPS as the academic baseline. Second, each contract was read for the CLOs and nine AI topic areas (T1–T9), and topic depth was assigned from explicitly documented learning activities: C1 for initial exposure, C2 for conceptual understanding, C3 for application or problem solving, and C4 for analysis, evaluation, design, or artifact development. These levels describe what the contract specifies; they are not direct measurements of a student's cognitive competence or exact equivalents of every domain in the RPS taxonomy.

Third, the same operational categories were used to classify contract design features. D described the lecturer role (D0–D4), A the intended AI role (A1–A4), M the assessment

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method (M0–M4), K the evaluation criteria (K0–K4), and R rubrication (R0–R4). Heutagogical opportunities were examined through separate indicators for learning opportunities, resource exploration, and explicitly self-selected learning paths; the V mark indicated an explicitly present indicator, while a dash or zero category indicated that the relevant information was not identified in the written evidence. The categories were treated as qualitative descriptors; a higher numeral was not assumed to establish superior overall student performance.

Fourth, the resulting classification records were compared across students and triangulated with available artifacts or answers and assessment records. Ambiguous descriptions were re-examined against the original documents and the operational definitions, rather than inferred from a student's grade. Descriptive counts were then aggregated to identify recurring patterns and contrasting cases. This stepwise procedure links each reported category back to the contract content and associated evidence and follows the principles of systematic qualitative data organization [17].

2.7. Trustworthiness and Ethical Considerations

Trustworthiness was addressed through consistent operational definitions, repeated examination of ambiguous documentary evidence, source triangulation, and traceability. Coding was undertaken by the academic supervisor using the same extraction framework across all 28 Learning Contracts. When a classification was unclear, the documentary evidence was re-examined in relation to the operational code definitions and, where relevant, the RPS/CLO baseline, submitted artifacts, or scores. Records of extraction and classification decisions supported an audit trail, and contrasting cases were retained rather than forced to conform to majority patterns. This document-based strategy supports interpretive transparency but does not constitute formal expert or psychometric validation of the coding scheme.

Students were anonymized as M001–M028. The study reported aggregate learning-design patterns and used student documents and achievement records within the scope of academic analysis. Because AI prompts and draft histories were unavailable, the analysis did not attribute specific decisions to AI or infer students' unobserved motivations. As the classification was conducted by one coder, there were no inter-coder disagreements to adjudicate; inter-rater reliability was therefore not calculated. Interpretive subjectivity was addressed through the documented operational definitions, repeated reading, and cross-checking of available evidence.

2.8. Data Analysis

The analysis combined qualitative document interpretation with descriptive summaries. Contract categories were counted across the 28 students and compared by CLO, topic area, learning depth, lecturer/AI role, evaluation method, criteria, rubrication, and

documented heutagogical opportunities. The analysis examined which learning choices extended the RPS while remaining aligned with CLOs and which planned artifacts had corresponding observable evidence. Horizontal, vertical, or mixed breadth–depth tendencies were interpreted only when supported by the extracted contract content.

Achievement data were summarized for Quiz 1, Quiz 2, Assignment 1, Assignment 2, Project, and the final weighted score. The existing assessment weights were 10%, 10%, 20%, 20%, and 40%, respectively. Scores were used to contextualize the realization of plans and to explore contrasts between contract characteristics and achieved grades. They were not used to infer causality, establish that AI improved performance, or replace the document-based assessment of learner agency. The final synthesis assessed the extent to which the available evidence supported self-determined learning within the limits of a single-course study.

3. RESULTS AND DISCUSSION

3.1. Baseline Course Structure and Intervention Data

The existing semester learning plan (RPS) provided the academic baseline for this evaluation. It specified five Course Learning Outcomes (CLOs), course content, assessment activities, and weights: Quiz 1 (10%), Quiz 2 (10%), Assignment 1 (20%), Assignment 2 (20%), and Project (40%). The complementary AI-assisted Learning Contract did not replace this structure. Instead, students documented individual learning choices, while their available quizzes, assignments, and projects provided evidence against which the written plans could be examined. The evaluative unit was the final Learning Contract of each of 28 students, anonymized as M001–M028.

The analysis distinguished alignment from personalization. A contract could cover the required CLOs without explicitly describing a distinct learning pathway. Conversely, resource or topic variation was considered meaningful only when linked to the intended CLO. This distinction prevents either compliance with the syllabus or variation in sources from being treated alone as proof of self-determined learning.

3.2. Operational Coding Scheme

The extraction codes functioned as descriptive classifications of what was explicitly documented in the Learning Contracts; they were not combined into a student-quality score. Table 3 condenses their operational meanings. Depth codes C1–C4 were read from stated learning activities, while D, A, M, K, and R described the contract design. The V indicator was examined separately for learning opportunities, exploration of learning resources, and explicitly self-selected paths. When evidence was not identifiable, it was not assumed to be absent from students' unrecorded activities.

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Table 3. Operational coding categories applied to the Learning Contracts.

Code group	Operational classification
C1–C4 (depth)	C1: basic exposure; C2: understanding; C3: application/problem solving; C4: analysis, evaluation, design, or artifact creation.
D0–D4 (lecturer)	D0: not specified; D1: role label; D2: generic function; D3: structured facilitator/evaluator; D4: activity/project mentor.
A1–A4 (AI)	A1: basic tool support; A2: pedagogical assistance; A3: technical/project support; A4: reflective-ethical partnership.
M0–M4 (method)	M0: not stated; M1: general/single method; M2: multiple methods listed; M3: CLO-aligned; M4: integrated formative–summative.
K0–K4 (criteria)	K0: not stated; K1: generic; K2: threshold-based; K3: CLO/task-specific; K4: analytical/multidimensional.
R0–R4 (rubric)	R0: no rubric; R1: checklist; R2: threshold; R3: performance levels; R4: analytic rubric with descriptors.
V / – (opportunities)	V: relevant heutagogical opportunity explicitly documented; –: not explicitly identified in the source document.

3.3. CLO Coverage and Documented Learning Depth

The five CLOs were strongly represented in the final contracts, but coverage was not complete for every student. CLO-1 to CLO-4 appeared in all 28 contracts; CLO-5 appeared in 27. Thus, 27 of 28 students (96.4%) documented all five CLOs, rather than 28 of 28. Table 4 records the maximum depth identified for each CLO. CLO-1 was predominantly at C2 (27 contracts), whereas CLO-5 included 17 contracts at C4 and 10 at C3. This distribution is compatible with the shift in planned activity from conceptual foundations toward application and artifact development. It does not prove that individual students attained those cognitive levels, and C2–C4 should not be treated as exact equivalents of every cognitive, affective, and psychomotor objective in the RPS.

Table 4. CLO coverage and maximum documented learning depth (n = 28).

CLO	C2	C3	C4	Not identified	Coverage
CLO-1	27	1	0	0	28 (100%)
CLO-2	0	14	14	0	28 (100%)
CLO-3	5	18	5	0	28 (100%)
CLO-4	1	14	13	0	28 (100%)
CLO-5	0	10	17	1	27 (96.4%)

3.4. Topic Distribution and Variation in Depth

The nine topic groups were T1 AI foundations, T2 AI for decision support/information systems, T3 search and problem solving, T4 knowledge representation, T5 predicate logic and inference, T6 probabilistic reasoning, T7 machine learning fundamentals, T8 applied AI/data workflow/model evaluation, and T9 ethics, impact, and sustainability. Figure 2 reproduces the coded topic-level counts from the extraction matrix. Each topic contains 28 classifications, including those assigned the basic-exposure level C1.

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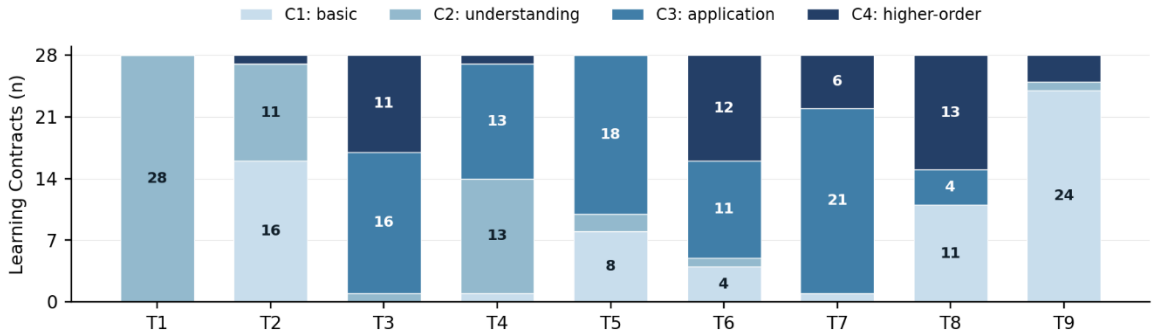


Figure 2. Learning topic distribution (T1–T9) by documented depth, based on the thesis extraction matrix.

The distribution suggests a greater orientation toward application and higher-order activity in T3, T6, T7, and T8. For example, T7 had 21 contracts at C3 and six at C4, while T8 had 13 at C4 but 11 at C1, indicating marked variation. T9 was concentrated at C1 (24 contracts), with only three at C4. The relatively limited depth of ethics and sustainability is a substantive design gap: technical exploration was more visible in written plans than critical assessment of AI consequences, governance, or responsibility.

3.5. Learning Contract Design Quality

Design quality was evaluated multidimensionally rather than as a single score. Table 5 reports the full distributions for lecturer role, AI role, evaluation method, criteria, and rubrication. Lecturer roles were commonly structured (D3: 13 contracts; D4: five), although six contracts did not specify a lecturer role (D0). Assessment methods were CLO-aligned or integrated (M3–M4) in 22 contracts, and specific or multidimensional criteria (K3–K4) appeared in 24. Rubrication was less uniform: 13 contracts used threshold rubrics (R2), 11 analytic rubrics (R4), and four had no rubric (R0). These results support evaluability, but demonstrate that the availability of evaluation criteria and explicit personalization are different qualities.

Table 5. Distribution of Learning Contract design indicators (28 contracts per dimension).

Aspect	Observed categories: number of students	Most common category
Lecturer role (D)	D0: 6; D1: 1; D2: 3; D3: 13; D4: 5	D3 (13)
AI role (A)	A1: 3; A2: 13; A3: 7; A4: 5	A2 (13)
Evaluation method (M)	M1: 1; M2: 5; M3: 16; M4: 6	M3 (16)
Evaluation criteria (K)	K1: 2; K2: 2; K3: 13; K4: 11	K3 (13)
Rubrication (R)	R0: 4; R2: 13; R4: 11	R2 (13)

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3.6. AI Roles and Human Oversight

AI was most often described as a pedagogical assistant (A2, 13 contracts), followed by a technical/project facilitator (A3, seven), a reflective-ethical partner (A4, five), and a basic tool (A1, three). The dominance of A2 suggests that students expected AI to help explain concepts, structure ideas, and provide initial feedback. Yet explicit reflective-ethical use was relatively uncommon. Because the records did not include prompt histories or document revisions, the classification describes the role students assigned to AI in their final contract; it cannot establish the share of work performed by AI or students. The design implication is to strengthen prompts for source checking, rationale for decisions, and human review rather than assume that AI access itself generates reflective practice.

3.7. Student Learning Achievement

Course scores were used as contextual evidence for the realization of learning activities, not as a measure of heutagogical competence or causal intervention effects. Table 6 reports the descriptive statistics available in the thesis. Project scores were uniformly high (mean 92.14; range 90–95), whereas Quiz 2 showed a mean of 59.46 despite a median of 80.00, indicating substantial influence from low or zero recorded values. The underlying administrative reasons for zeros were not documented, and they were therefore retained rather than attributed to absence or lack of learning.

Table 6. Descriptive statistics for the existing course assessments (n = 28).

Assessment	Mean	Median	Minimum	Maximum
Quiz 1	71.79	70.00	0.00	95.00
Quiz 2	59.46	80.00	0.00	95.00
Assignment 1	86.00	95.00	0.00	95.00
Assignment 2	61.07	67.25	18.00	89.00
Project	92.14	90.00	90.00	95.00
Final weighted grade	79.40	79.12	42.20	90.80

Contrasting cases reinforce this distinction. Student M007 had a reflective-ethical AI role (A4) and a final grade of 90.80, whereas M025 also had A4 and a relatively structured evaluation profile but a final grade of 42.20. A strong written contract thus did not guarantee equivalent performance. The analysis did not infer correlations or intervention efficacy from such small descriptive groups; achievement records were interpreted alongside the contract and artifact evidence.

3.8. Learning Contract as an Information Artifact

The Learning Contract functioned as more than an administrative agreement. It recorded structured relationships between CLOs, personal goals, selected topics, learning resources, AI and lecturer roles, expected artifacts, evaluation methods, and rubrics. This

made it possible to compare formal course expectations with planned student decisions and observable evidence. In educational information systems terms, the value lies in the traceable organization of learning choices, which is relevant to curriculum analytics and learning analytics research emphasizing aligned data sources and stakeholder-oriented interpretation [12], [13]. The present work demonstrates the feasibility of structuring these data in an evaluation matrix; it does not report the deployment of an automated learning analytics platform.

3.9. Support for Self-Determined Learning

Support for self-determined learning was uneven across its observable dimensions. All 28 contracts included resource exploration, and 22 described learning opportunities such as discussions, assistance, or additional activities. Only three explicitly indicated an individually determined learning path. As summarized in Table 7, the strongest documented support concerned resource autonomy, CLO alignment, and evaluability; explicit pathway autonomy and reflective AI use remained comparatively limited. The absence of an explicit Own Path indicator in a final document cannot prove that a student never made personal decisions, but undocumented decisions cannot be credited as observed evidence.

Table 7. Heutagogical learning opportunities identified in final Learning Contracts.

Documented indicator	Contracts (n = 28)	Proportion
Explore Resources	28	100.0%
Learning Opportunities	22	78.6%
Explicit Own Path	3	10.7%

The distinction between resource autonomy and pathway autonomy is important. Students could explore different resources without explicitly articulating why an individual route was selected, how it evolved, or how it differed from the default course sequence. Similarly, a contract with a well-defined rubric could be highly evaluable but not necessarily more personalized. These patterns indicate structured but partial support for self-determined learning rather than evidence that all participants had become self-determined learners.

3.10. AI Integration and Responsible Learning

The combination of frequent AI pedagogical assistance (A2) and limited reflective-ethical positioning (A4) suggests that technology support and responsibility require separate attention. Reflection could be strengthened by asking students to identify AI-assisted steps, verify sources, evaluate outputs against disciplinary criteria, and explain decisions that remain under human control. These are implications for a subsequent iteration of the method, not procedures observed for every participant in the present

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intervention. The shallow representation of T9 also supports closer integration of ethical and sustainability considerations into future Learning Contract guidance.

3.11. Contribution to Educational Information Systems

The study contributes a course-level view of a Learning Contract as a socio-technical boundary between institutional outcomes and individualized learning decisions. People are represented by student choice and lecturer oversight; Process by CLO-aligned planning, artifact production, and evaluation; and Technology by AI-supported exploration and structured documentation. The practical information-systems contribution is a traceable specification of data elements and relationships that can support future monitoring and feedback. For example, a digital contract-builder could flag a missing CLO mapping, an absent assessment criterion, or an unrecorded AI role, while a lecturer dashboard could display patterns of depth or rubric completeness. Such capabilities are proposed design directions, not implemented or validated software components. Their development would also require attention to human review and the governance of student learning data [12], [13], [18].

3.12. Limitations and Future Research

This evaluation concerned one postgraduate AI course with 28 students, limiting statistical generalizability. The primary evidence comprised final Learning Contracts and available course documents, artifacts, and scores; AI prompts, early drafts, revision histories, and continuous process logs were not available. Accordingly, actual human–AI contributions and longitudinal changes in learner agency could not be reconstructed. No control group or longitudinal psychometric measure was used, and the observed score patterns do not establish causality. The operational codes were developed for this context and require examination in other courses and institutions before broader transfer is claimed. Future work may test the method with repeated contract revisions, documented AI contributions, independent coding, interviews, and a digital learning-contract platform linked to learning analytics. Those extensions should preserve student decision ownership and lecturer oversight.

4. CONCLUSION

This study evaluated a heutagogy-informed, AI-assisted Learning Contract as a complementary mechanism within an existing postgraduate Artificial Intelligence course. The semester learning plan (RPS), five Course Learning Outcomes (CLOs), Lecture and Brainstorming activities, and established assessments were retained. Twenty-seven of 28 final Learning Contracts documented all five CLOs, while the coded topic profiles showed variation in learning depth. The results indicate that course-level academic alignment can

be maintained while students articulate different resources, learning activities, and intended artifacts.

Support for self-determined learning was partial rather than uniform. All 28 contracts indicated resource exploration, and 22 described learning opportunities, but only three explicitly articulated an individual learning path. AI was most frequently positioned as a pedagogical assistant (13 contracts), with reflective-ethical support identified in five. Ethics and sustainability also remained predominantly at a basic level, and four contracts lacked rubrics. Thus, resource autonomy and evaluability were more visible than explicit pathway autonomy and reflective AI accountability. The final-grade mean of 79.40 characterized achievement in this class; it was not treated as evidence of a causal effect of the intervention.

The contribution lies in treating the Learning Contract as a socio-technical pedagogical and information artifact that connects CLOs, student decisions, lecturer oversight, AI support, and learning evidence. This documented structure can inform future contract-building, monitoring, and learning-analytics mechanisms, but no such digital system was implemented or evaluated here. Findings are limited to one class and final contracts without complete AI prompt logs, contract revision histories, a control group, or longitudinal self-determined learning measures. Future research should evaluate the method across settings and document how learning pathways and human–AI decisions evolve over time.

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