PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

Smart Sequencing of Social Media Microlearning for Higher Education: A Transparent Constraint-Based Algorithm

Serap Uğur[1*]
[1]Anadolu University, Türkiye
[1*]serapsisman@anadolu.edu.tr

open access

***Corresponding Author**

Article History:
Submitted: 24-09-2026
Accepted: 30-09-2026
Published: 04-01-2027

Keywords:
content sequencing; higher education; microlearning; social media learning; transparent algorithm.

PERFECT: Journal of Smart Algorithms is licensed under a Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0).

ABSTRACT

Social media can extend learning beyond formal higher education settings, but platform-generated content order does not necessarily create a coherent pathway. This limitation is particularly important for social media learning based on brief microlearning objects. This study developed and computationally evaluated a transparent algorithm for content sequencing without using learner profiles, behavioral records, or institutional data. A controlled benchmark of 24 researcher-constructed objects on misinformation and digital verification was organized across seven themes and 42 prerequisite relations. The proposed algorithm restricted eligibility according to prerequisite satisfaction and cognitive stage, then selected among eligible objects using semantic continuity, difficulty smoothness, thematic coverage, and pedagogical content-type diversity. Its output was compared with random, prerequisite-only, semantic-only, and cognitive-only sequencing through six structural metrics, 1,771 weight configurations, and component-ablation tests. The proposed method produced no prerequisite violations, cognitive regressions, or large upward difficulty jumps. Prerequisite-only sequencing eliminated prerequisite violations but yielded a mean cognitive regression rate of .187, while semantic-only sequencing achieved the highest textual continuity but violated 57.1% of prerequisite relations. Rank correlations with the default sequence ranged from .976 to 1.000, and 537 weight configurations reproduced it exactly. The algorithm transparently balanced structural constraints and preference criteria within the benchmark. The findings verify its specified decision rules but do not establish improved human learning.

INTRODUCTION

Social media has become part of the environment in which university learners encounter explanations, demonstrations, verification practices, and other forms of educational microcontent. Recent reviews indicate that social media is increasingly used for teaching and learning in higher education, although its educational value depends on pedagogical integration rather than platform use alone (Denojean-Mairet et al., 2024; Perez et al., 2023). Short-form content delivered through platforms such as TikTok has also been integrated into university courses and evaluated in terms of educational use, learner satisfaction, and technology acceptance (Conde-Caballero et al., 2024). Nevertheless, the availability of relevant educational content does not ensure that multiple objects collectively form an intelligible learning pathway.

This problem reflects a mismatch between platform-generated ordering and instructional sequencing. Social media feeds are generally organized around platform relevance and user engagement rather than explicit instructional dependencies. Their ordering mechanisms therefore do not inherently represent prerequisite relations, cognitive progression, or productive transitions among explanation, demonstration, and practice. Consequently, a feed may contain individually relevant items while presenting them in an educationally weak order. An application may precede its conceptual foundation, a complex verification procedure may appear before its component skills, or repeated explanations may displace opportunities to apply and integrate knowledge.

Sequencing is especially consequential in microlearning because the brevity of individual objects transfers much of the burden of coherence to the relations among them. A short object can communicate a bounded idea, but it cannot independently establish the prerequisite structure, conceptual transitions, and pedagogical variation of a longer learning experience. In social media settings, sequencing therefore determines whether distributed microcontent can function as a pathway rather than merely as a collection of posts.

Educational recommender systems offer numerous methods for constructing learning paths, but their dominant objective is personalization. Resources are commonly selected or sequenced according to learner profiles, previous performance, interaction traces, estimated knowledge states, or relationships represented in educational knowledge graphs (Chen et al., 2023; Zhang et al., 2023). Recent studies have also incorporated prerequisite relations and learning-

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

object metadata into recommendation processes (Chanaa & El Faddouli, 2024). Although these approaches demonstrate the sophistication of contemporary learning-path recommendation, they may require learner-interaction data, structured knowledge representations, or expert annotation, which can restrict their application when these resources are unavailable (Vassoyan et al., 2024).

Addressing this content-side problem requires more than selecting the most semantically similar next object. Semantic similarity is symmetric, whereas prerequisite relations are directional: two objects may be closely related even though one presupposes the other. Cognitive level provides an additional ordering signal, but sorting only by cognitive demand cannot resolve dependencies among objects at the same level and may produce repetitive stretches of the same pedagogical form. The sequencing problem is therefore multi-criteria but not fully compensatory. Prerequisite satisfaction and cognitive staging should restrict the set of permissible choices, while semantic continuity, difficulty smoothness, thematic coverage, and pedagogical variety should distinguish among eligible alternatives.

This study develops and computationally evaluates the Smart Microlearning Sequence Algorithm (SMSA), a transparent procedure for organizing a fixed set of social-media-compatible microlearning objects without using learner profiles, behavioral records, or institutional data. SMSA combines prerequisite-feasible topological selection with cognitive staging and an inspectable multi-criteria rule. It is positioned as a domain-specific constrained sequencing procedure rather than as a general-purpose optimization algorithm. Its contribution lies in separating non-compensatory eligibility conditions from preference criteria and providing a reproducible framework for examining their individual effects.

The evaluation compares SMSA with random, prerequisite-only, semantic-only, and cognitive-only sequencing. It examines whether SMSA satisfies its encoded prerequisite and cognitive-stage constraints; how its structural properties compare with those of the four baselines; what trade-offs it produces among semantic continuity, difficulty smoothness, thematic switching, and content-type diversity; and how sensitive its sequence is to alternative criterion weights and component removal. These questions are investigated through structural metrics, a systematic weight-grid analysis, and component-ablation tests.

The study evaluates formal properties of the generated sequences rather than achievement, motivation, retention, engagement, or cognitive load. Structural coherence is treated as a testable design property and a prerequisite for, rather than evidence of, educational effectiveness. This boundary enables a reproducible first-stage evaluation without personal or institutional data while establishing a basis for subsequent validation with learners.

LITERATURE REVIEW

Social Media Microlearning

Social media combines information discovery, content creation, interaction, and educational participation within the same digital environments. A recent systematic review shows that social media has become an established teaching and learning resource in higher education, while also emphasizing that its educational value depends on theoretically and pedagogically informed use (Perez et al., 2023). Educational content in these environments is nevertheless commonly distributed as short, independently accessible units rather than as deliberately ordered learning pathways.

Microlearning organizes educational content around brief, focused, and manageable learning activities. Its educational value does not result from brevity alone but from the alignment of content, learning objectives, activities, and intended outcomes (Alias & Abdul Razak, 2023). Recent research in higher education reports positive learner satisfaction and perceived effectiveness when microlearning is deliberately designed and integrated into instruction (Rof et al., 2024). A review of social media–microlearning integration similarly shows that short-form content can support reach, engagement, and learning, while cautioning that pedagogical coherence and theoretical grounding remain insufficiently examined (Denojean-Mairet et al., 2024).

In this study, a microlearning object is defined as an identifiable instructional unit with a specific learning purpose and metadata describing its theme, content type, cognitive level, difficulty, duration, and prerequisite relations. The benchmark focuses on misinformation and digital verification and covers fact-checking, information disorder, artificial intelligence, digital citizenship, and responsible social media participation. It represents an illustrative computational collection rather than an officially validated curriculum.

Learning-Object Sequencing

Learning-path research distinguishes the identification of relevant resources from their organization into an instructional order. Contemporary approaches use concept representations, knowledge graphs, prerequisite relations, and sequence-generation models to construct learning pathways (Chanaa & El Faddouli, 2024; Chen et al., 2023; Zhang et al., 2023). A collection of individually relevant objects may still form a weak pathway if dependencies, cognitive progression, difficulty transitions, and pedagogical variation are ignored.

Cognitive progression offers another basis for sequencing. The revised Bloom's taxonomy distinguishes remembering, understanding, applying, analyzing, evaluating, and creating. However, these categories should not be interpreted as an inflexible linear hierarchy because cognitive processes may overlap and progression may vary

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

according to task and knowledge type (Larsen et al., 2022). In SMSA, the categories therefore function as an explicit sequencing convention rather than as a claim that all learning necessarily proceeds through a fixed series of stages. Nevertheless, abrupt progression to advanced tasks or repeated regression after advanced activity begins may indicate weak organization within a short learning pathway. Difficulty is related to cognitive level but is not identical to it. Objects at the same cognitive level may differ in procedural complexity or in the number of interacting information elements that must be coordinated. Contemporary cognitive load theory therefore emphasizes the relationship among prior knowledge, task complexity, working-memory demands, and instructional design (Sweller, 2024).

A viable sequence must also balance continuity and variation. Abrupt thematic transitions may produce fragmentation, whereas repeated presentation of highly similar objects or the same pedagogical content type may create redundancy. Sequencing should therefore preserve necessary dependencies while avoiding unnecessary repetition and unsupported changes in difficulty or cognitive demand.

Transparent Multi-Criteria Sequencing

Recent learning-path systems use learner profiles, interaction histories, performance records, knowledge tracing, concept representations, and knowledge graphs to generate personalized pathways (Chen et al., 2023; Zhang et al., 2023). These approaches are appropriate when reliable learner-level information is available. They are less directly applicable when a fixed collection must be organized before learner interaction occurs. Recent research also identifies dependence on learner data or expert annotation as a limitation affecting the broader use of adaptive sequencing models (Vassoyan et al., 2024). SMSA addresses this earlier content-design stage without estimating learner characteristics or mastery.

Prerequisite relations can be represented as a directed graph in which an edge indicates that one concept or learning object should precede another, as demonstrated in recent educational knowledge-graph and prerequisite-based recommendation research (Aytekin & Saygın, 2024; Chanaa & El Faddouli, 2024). When this graph contains no directed cycles, a complete feasible pathway must place each object after all of its specified prerequisites. SMSA applies this condition iteratively by admitting an unused object to the feasible set only after all its prerequisites have been placed. Educational sequencing introduces an additional decision problem because several prerequisite-feasible objects may be available simultaneously. SMSA addresses this problem by distinguishing hard constraints from soft preferences. Prerequisite satisfaction and cognitive staging determine eligibility, whereas semantic continuity, difficulty smoothness, thematic coverage, and content-type diversity distinguish among eligible candidates. Consequently, a favorable score on a soft criterion cannot compensate for an unsatisfied prerequisite.

Semantic continuity is represented through term frequency–inverse document frequency and cosine similarity, which remain commonly used for metadata-based matching in content-oriented educational recommendation (Chanaa & El Faddouli, 2024). Similarity functions as a local continuity signal rather than evidence of pedagogical equivalence or directional dependence. The remaining criteria rely on explicit object metadata and recent selections in the developing pathway. This design makes each decision traceable to eligibility rules, criterion scores, and tie-breaking procedures.

Explainability is increasingly important in educational artificial intelligence because it can affect trust, acceptance, and the capacity of learners and educators to evaluate system outputs (Khosravi et al., 2022; Takami et al., 2023). SMSA pursues intrinsic transparency: its rules, weights, candidate scores, and final selections are inspectable without post-hoc explanation. The term smart algorithm consequently refers to structured, context-sensitive decision-making across multiple criteria, not autonomous intelligence or demonstrated adaptation to individual learners.

The conceptual framework thus combines microlearning design, prerequisite representation, cognitive progression, information retrieval, and transparent multi-criteria selection. It supports evaluating whether a constraint-first procedure can preserve directional relations while balancing continuity and pedagogical variation among eligible learning objects.

METHOD

The study used a computational design-and-evaluation approach to develop and test a transparent sequencing algorithm for social-media-compatible microlearning objects. The process comprised benchmark construction, metadata representation, pathway generation with five sequencing methods, and comparison through structural metrics. The unit of analysis was the microlearning object. No learner profiles, institutional records, surveys, interviews, observations, social media accounts, or behavioral traces were used.

The controlled benchmark comprised 24 researcher-constructed objects concerning misinformation and digital verification. Seven thematic units covered foundations, spread mechanisms, cognitive safeguards, verification, synthetic media, responsible action, and integration. Each object had an identifier, title, description, thematic unit, pedagogical content type, cognitive level, difficulty, estimated duration, and prerequisite list. Cognitive levels ranged from remembering to creating based on the cognitive-process dimension of the revised Bloom's taxonomy, while difficulty was represented separately on a five-level ordinal scale (Larsen et al., 2022). Duration was retained as descriptive

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

metadata but was not used in scoring.

A directed relation $j \rightarrow i$ indicated that object j was specified as a prerequisite of object i. The benchmark contained 42 such relations. All identifiers referred to objects within the collection, and no relation required an object at a higher cognitive level to precede one at a lower level. The benchmark was constructed to examine the sequencing procedure and should not be interpreted as learner data or an independently validated curriculum.

Text Representation and Semantic Similarity

For each object, the title, description, and thematic label were combined and represented as term frequency–inverse document frequency vectors containing unigrams and bigrams after removal of common English stop words. The cosine similarity between objects $i$and $j$was calculated as

$$\text{sim}(i, j) = \frac{\boldsymbol{v}_i \cdot \boldsymbol{v}_j}{\| \boldsymbol{v}_i \| \| \boldsymbol{v}_j \|},$$

where $\boldsymbol{v}_i$and $\boldsymbol{v}_j$are their TF–IDF vectors. Higher values indicate greater textual overlap. Vectorization and similarity calculations were implemented using scikit-learn (Pedregosa et al., 2011). Similarity served as an indicator of local textual continuity; it did not determine prerequisite direction or establish pedagogical validity.

Sequencing Methods

Five methods generated complete sequences of the 24 objects. Random sequencing shuffled all identifiers without using metadata or prerequisites. Prerequisite-only sequencing randomly selected an unused object whose prerequisites had already been placed, thereby isolating the effect of graph feasibility without cognitive staging or preference scoring. Cognitive-only sequencing ordered objects by ascending cognitive level and then difficulty, with identifiers shuffled within groups sharing both values. These three stochastic methods were each repeated 1,000 times using integer seeds from 0 to 999, and means and sample standard deviations were calculated.

Semantic-only sequencing used deterministic greedy nearest-neighbor selection. Its first object was selected by similarity to a predefined learning-goal statement concerning misinformation, social media algorithms, verification, and responsible sharing. Each subsequent step selected the unused object most similar to the preceding object. Ties were resolved using the lowest identifier. This method did not use prerequisites, cognitive level, difficulty, theme, or content type.

Smart Microlearning Sequence Algorithm

SMSA constructed a pathway one object at a time. At step (t), it identified the set (F_t) of unused objects whose prerequisites had been placed and retained those at the lowest cognitive level represented in (F_t). The resulting objects formed candidate set (C_t). If no feasible object existed before completion, the procedure stopped and reported an invalid prerequisite graph.For each candidate $i \in C_t$, SMSA calculated

$$S_t(i) = 0.35\, SC_t(i) + 0.30\, PD_t(i) + 0.20\, DS_t(i) + 0.15\, TC_t(i),$$

where *SC* denotes semantic continuity, *PD* denotes content-type diversity, *DS* denotes difficulty smoothness, and *TC* denotes thematic coverage. The weights were researcher-defined design parameters; they were not estimated from learner data and were subsequently examined through sensitivity analysis.

Except at the first position, semantic continuity was the cosine similarity between the candidate and the most recently selected object. It was set to 0 at the first position. Content-type diversity was 1 when the candidate's type differed from the types of both of the two most recently selected objects, and 0 otherwise; it was set to 1 at the first position. With candidate difficulty $d_i$and preceding difficulty d_{t-1}, difficulty smoothness was

$$DS_t(i) = 1 - \frac{|\, d_i - d_{t-1}\,|}{4},\ t > 1.$$

At the first position, the implementation favored lower difficulty:

$$DS_1(i) = 1 - \frac{d_i - 1}{4}.$$

Thematic coverage equaled one when the candidate's theme had not previously appeared and zero otherwise. The highest-scoring candidate was selected, with ties resolved using the lowest identifier. Prerequisite satisfaction and

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

cognitive staging therefore restricted eligibility, whereas the four weighted criteria distinguished among eligible objects. Difficulty smoothness remained a preference rather than a prohibition on large jumps. Figure 1 presents the complete selection cycle.

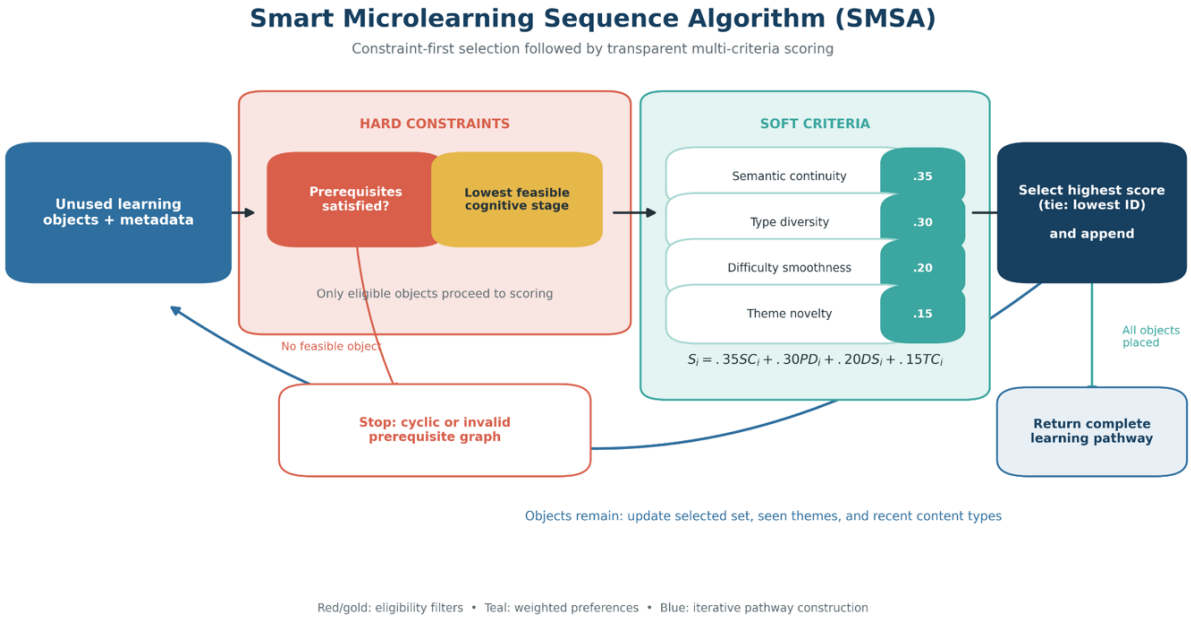


Figure 1. Workflow of the Smart Microlearning Sequence Algorithm

The cycle continues until all objects have been placed or no feasible object remains.

Evaluation Metrics

Let the completed sequence be $\pi = (\pi_1, \ldots, \pi_N)$, where $N = 24$. Let Rbe the set of directed prerequisite relations, with $| R | = 42$, and let $\text{pos}_\pi(i)$be the position of object i. The remaining metrics were calculated over the $N - 1 = 23$adjacent transitions. Here, $\mathbb{1}[\cdot]$equals 1 when the stated condition holds and 0 otherwise.

Prerequisite Violation Rate (PVR) was the proportion of directed relations in which the dependent object appeared before its prerequisite:

$$\text{PVR}(\pi) = \frac{1}{| R |} \sum_{(j,i) \in R} \mathbb{1}\left[\text{pos}_\pi(i) < \text{pos}_\pi(j)\right].$$

Large Difficulty Jump Rate (LDJR) was the proportion of adjacent transitions in which difficulty increased by more than one level:

$$\text{LDJR}(\pi) = \frac{1}{N-1} \sum_{t=1}^{N-1} \mathbb{1}\left[d_{\pi_{t+1}} - d_{\pi_t} > 1\right].$$

Cognitive Regression Rate (CRR) was the proportion of transitions to a lower cognitive level:

$$\text{CRR}(\pi) = \frac{1}{N-1} \sum_{t=1}^{N-1} \mathbb{1}\left[c_{\pi_{t+1}} < c_{\pi_t}\right].$$

Mean Semantic Continuity (MSC) was the mean cosine similarity of adjacent objects:

$$\text{MSC}(\pi) = \frac{1}{N-1} \sum_{t=1}^{N-1} \text{sim}\left(\pi_t, \pi_{t+1}\right).$$

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

Adjacent Type Repetition Rate (ATRR) was the proportion of transitions between objects with the same pedagogical content type:

$$\mathrm{ATRR}(\pi) = \frac{1}{N-1}\sum_{t=1}^{N-1} \mathbb{1}\left[p_{\pi_{t+1}} = p_{\pi_t}\right].$$

Thematic Switch Rate (TSR) was the proportion of transitions between different thematic units:

$$\mathrm{TSR}(\pi) = \frac{1}{N-1}\sum_{t=1}^{N-1} \mathbb{1}\left[h_{\pi_{t+1}} \neq h_{\pi_t}\right].$$

Here d_i, c_i, p_i, and $h_i$denote object i's difficulty, cognitive level, content type, and thematic unit, respectively. Lower PVR, LDJR, CRR, and ATRR values describe fewer occurrences of the corresponding structural events. Higher MSC indicates greater adjacent textual similarity. TSR was interpreted descriptively because a higher or lower switching rate is not inherently preferable.

The preference criteria used during SMSA selection were related to, but not identical with, the evaluation metrics. Content-type diversity considered the two most recently selected objects, whereas ATRR measured immediate adjacency. Difficulty smoothness penalized absolute differences in either direction, whereas LDJR recorded only upward jumps greater than one level. Thematic coverage rewarded the first appearance of a theme, whereas TSR measured changes between adjacent themes. The evaluation metrics were therefore used as complementary descriptions of the complete sequences rather than as direct restatements of the candidate-level scoring functions.

Sensitivity, Ablation, Reproducibility, and Ethical Scope

A systematic weight-grid analysis varied the four nonnegative criterion weights in increments of .05 while requiring their sum to equal one, producing 1,771 configurations. SMSA generated a sequence for each configuration, after which the six metrics, number of distinct sequences, frequency of the default sequence, and Spearman rank correlation with the default object positions were calculated.

Component ablation removed one soft criterion at a time by assigning it a weight of zero and normalizing the remaining weights to sum to one. Each resulting sequence was compared with the default SMSA pathway using the six metrics and rank correlation. Prerequisite feasibility and cognitive staging remained unchanged in both analyses.

Benchmark records, prerequisite relations, parameters, random seeds, code, sequences, and metric calculations were retained. Fixed seeds governed stochastic methods, while semantic-only sequencing and SMSA used deterministic tie-breaking. Materials can be provided to editors and reviewers upon request and will be available from the corresponding author following publication.

Because the study involved no human participants, personal data, identifiable institutions, social media accounts, or observations of user behavior, ethics committee approval and informed consent were not applicable under the relevant institutional criteria. The findings describe algorithmic behavior within the constructed benchmark and do not demonstrate effects on learning, engagement, retention, or other learner outcomes.

RESULT

Comparison of Sequencing Methods

Table 1 presents the six structural metrics for the five sequencing methods. Results for random, prerequisite-only, and cognitive-only sequencing are means and sample standard deviations across 1,000 seeded runs. Semantic-only sequencing and SMSA were deterministic and each produced one sequence.

Table 1. Structural Performance of the Sequencing Methods

Method	PVR	LDJR	CRR	MSC	ATRR	TSR
Random, 1,000 runs	.502 (.076)	.157 (.050)	.411 (.063)	.022 (.007)	.081 (.055)	.884 (.067)
Prerequisite-only, 1,000 runs	.000 (.000)	.014 (.023)	.187 (.051)	.042 (.008)	.169 (.060)	.630 (.095)
Semantic-only	.571	.043	.391	.088	.087	.391
Cognitive-only, 1,000 runs	.095 (.034)	.000 (.000)	.000 (.000)	.037 (.008)	.252 (.054)	.698 (.063)
SMSA	.000	.000	.000	.044	.217	.696

Note. Values in parentheses are sample standard deviations. PVR = prerequisite violation rate; LDJR = large difficulty jump rate; CRR = cognitive regression rate; MSC = mean semantic continuity; ATRR = adjacent type repetition rate; TSR = thematic switch rate.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

Random sequencing violated approximately half of the prerequisite relations on average ($M = .502$, $SD = .076$) and produced cognitive regressions in approximately 41% of adjacent transitions ($M = .411$, $SD = .063$). It had the lowest mean semantic continuity ($M = .022$, $SD = .007$) and the highest thematic switch rate ($M = .884$, $SD = .067$). Its relatively low adjacent type repetition rate ($M = .081$) should be considered alongside these other results: frequent changes in content type did not, by themselves, preserve the benchmark's specified order.

Prerequisite-only sequencing satisfied all 42 directed relations across its 1,000 runs, as expected from its feasibility rule. However, prerequisite satisfaction alone did not maintain cognitive order: the method produced a mean cognitive regression rate of .187 ($SD = .051$). Its mean large difficulty jump rate was .014 ($SD = .023$) and its mean semantic continuity was .042 ($SD = .008$). These results separate the effect of enforcing prerequisite relations from the additional effect of SMSA's cognitive-stage restriction.

Semantic-only sequencing achieved the highest mean semantic continuity (MSC = .088). However, it placed the dependent object before its prerequisite in 24 of the 42 relations (PVR = .571) and produced cognitive regressions in 9 of the 23 adjacent transitions (CRR = .391). Within this benchmark, selecting the most textually similar next object therefore did not preserve the researcher-defined prerequisite and cognitive order.

Cognitive-only sequencing produced no cognitive regressions or large upward difficulty jumps across its 1,000 runs. Because it did not enforce prerequisite relations within groups sharing the same cognitive and difficulty levels, its mean prerequisite violation rate remained .095 ($SD = .034$). It also had the highest adjacent type repetition rate ($M = .252$, $SD = .054$), while its mean semantic continuity was .037 ($SD = .008$).

Within the benchmark, SMSA produced no prerequisite violations, cognitive regressions, or large upward difficulty jumps. Its prerequisite result was shared with the prerequisite-only baseline and followed directly from feasibility filtering. In contrast, SMSA's zero cognitive-regression rate differed from the prerequisite-only mean of .187, indicating the additional role of cognitive staging within this benchmark. SMSA produced slightly greater mean semantic continuity than prerequisite-only sequencing (.044 vs. .042), although prerequisite-only sequencing had a lower mean adjacent type repetition rate (.169 vs. .217). Thus, SMSA did not dominate every soft metric; it produced a different balance by combining prerequisite satisfaction and cognitive order with deterministic preference-based selection.

Figure 2 illustrates these structural differences. Prerequisite-only sequencing enforced the dependency graph but did not prevent cognitive regression, while cognitive-only sequencing protected cognitive order without guaranteeing prerequisite satisfaction. Semantic-only sequencing maximized local textual continuity at the expense of the encoded prerequisite and cognitive relations. SMSA was the only method that simultaneously produced zero values for PVR, LDJR, and CRR within the benchmark.

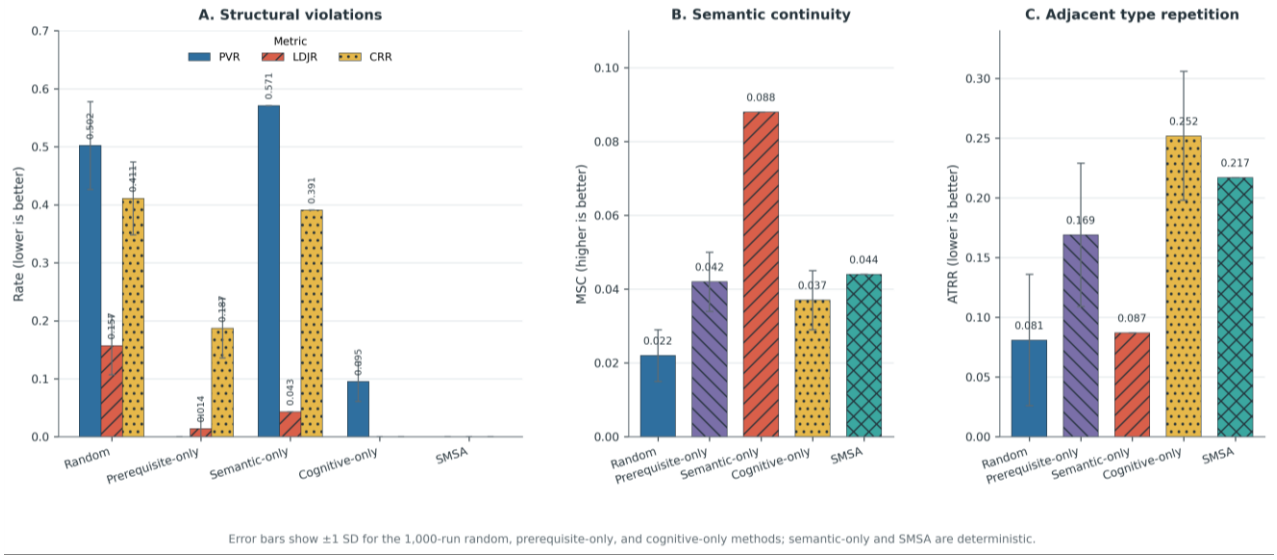


Figure 2. Structural Performance of the Five Sequencing Methods.

Panels show (A) prerequisite violation rate, large difficulty jump rate, and cognitive regression rate; (B) mean semantic continuity; and (C) adjacent content-type repetition rate. Error bars represent ±1 standard deviation for random, prerequisite-only, and cognitive-only sequencing across 1,000 seeded runs. Semantic-only sequencing and SMSA are deterministic.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

Robustness Under Alternative Criterion Weights

The systematic grid analysis evaluated 1,771 valid weight configurations and generated 34 distinct sequences. Among these configurations, 537 reproduced the default SMSA sequence exactly. Spearman rank correlations with the default sequence ranged from .976 to 1.000, with a median of .988 and a mean of .990.

PVR, LDJR, and CRR remained zero across all configurations. MSC ranged from .032 to .059, ATRR from .217 to .348, and TSR from .522 to .783. Thus, the eligibility rules preserved the three measured structural outcomes throughout the tested weight space, whereas changes in the soft-criterion weights affected continuity, repetition, and thematic transitions.

The limited variation in object order partly reflected the candidate-set structure. Under the default sequence, only one candidate was available at 11 of the 24 selection steps. The mean candidate-set size was 1.75 and the maximum was three; consequently, weights could affect selection only when multiple objects remained after prerequisite and cognitive-stage filtering.

Table 2. Results of the Systematic Weight-Sensitivity Analysis

Indicator	Result
Weight configurations	1,771
Distinct sequences	34
Configurations reproducing default sequence	537
Rank correlation, minimum	.976
Rank correlation, median	.988
Rank correlation, mean	.990
Rank correlation, maximum	1.000
MSC range	.032–.059
ATRR range	.217–.348
TSR range	.522–.783
PVR, LDJR, and CRR range	.000–.000

Component-Ablation Results

Table 3 compares the default sequence with sequences produced after removing individual soft criteria. PVR, LDJR, and CRR remained zero in every condition.

Table 3. SMSA Results After Removal of Individual Soft Criteria

Configuration	MSC	ATRR	TSR	Rank correlation
Default SMSA	.044	.217	.696	1.000
Without semantic continuity	.035	.217	.739	.988
Without type diversity	.043	.304	.696	.986
Without difficulty smoothness	.044	.217	.696	1.000
Without thematic coverage	.047	.261	.652	.980

Removing semantic continuity reduced MSC from .044 to .035, while removing content-type diversity increased ATRR from .217 to .304. Removing difficulty smoothness produced no change in object order or metric values. Removing thematic coverage increased MSC to .047, increased ATRR to .261, and reduced TSR to .652. The corresponding rank correlations with the default sequence ranged from .980 to 1.000. These results show that semantic continuity, content-type diversity, and thematic coverage affected the sequence characteristics within the benchmark, whereas difficulty smoothness was not decision-determining under the available candidate sets.

DISCUSSION

Structural Trade-offs in Learning-Object Sequencing

This study compared five procedures for organizing a constructed collection of social-media-compatible microlearning objects. The results distinguish among textual similarity, cognitive progression, and directed prerequisite relations, which provide related but non-equivalent signals for sequencing. SMSA satisfied the encoded prerequisite relations and produced no cognitive regressions or large upward difficulty jumps within the benchmark. Because prerequisite feasibility was built into the algorithm, the absence of prerequisite violations verifies the implementation of that rule rather than independently demonstrating pedagogical effectiveness.

Semantic-only sequencing achieved the highest local textual continuity but frequently placed dependent objects before their prerequisites. Cosine similarity indicates the degree to which two object texts share terms, whereas a prerequisite specifies the direction in which they should be encountered. This distinction is consistent with recent learning-path research showing that semantic relevance, prerequisite relations, concept structure, and sequence generation represent related but distinct components of educational recommendation (Chanaa & El Faddouli, 2024;

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

Chen et al., 2023; Zhang et al., 2023). Similarity can identify related materials and support continuity, but it cannot determine whether an explanation should precede its application.

Prerequisite-only sequencing preserved the dependency graph but allowed cognitive regression, while cognitive-only sequencing preserved cognitive order without fully satisfying the prerequisite relations. Objects at the same cognitive and difficulty levels could still be connected by directional dependencies. Cognitive-only sequencing also produced greater adjacent content-type repetition, indicating that cognitive process and instructional form describe different properties of a learning object. These findings support representing both properties when constructing short educational pathways.

The results should not be interpreted as requiring every learning experience to follow an invariably ascending cognitive path. Returning to foundational content may be instructionally appropriate. SMSA instead implements a specific rule for a common short pathway by selecting from the lowest cognitive level currently available after prerequisite filtering. Its structural behavior must therefore be interpreted in relation to this rule and the benchmark on which it was tested.

Constraint-First and Transparent Selection

The principal design contribution of SMSA is its separation of eligibility from preference. An object becomes eligible only when its prerequisites have been placed, after which cognitive staging further restricts the candidate set. Semantic continuity, content-type diversity, difficulty smoothness, and thematic coverage then differentiate among eligible objects. This order prevents a strong preference score from compensating for an unsatisfied prerequisite.

The distinction also makes the source of each outcome inspectable. A placement can be reconstructed from the prerequisite graph, object metadata, preceding selections, criterion weights, and tie-breaking rule. This intrinsic transparency differs from personalized learning-path systems that generate recommendations from learner histories, estimated mastery, knowledge tracing, or complex concept representations (Chen et al., 2023; Zhang et al., 2023). SMSA does not replace those approaches. It addresses an earlier design condition in which a common initial sequence is required before learner interaction or when learner-level data are unavailable.

Transparency is important in educational recommendation because educators and learners may need to evaluate why particular resources or activities were recommended (Khosravi et al., 2022; Takami et al., 2023). SMSA supports this evaluation by exposing its eligibility rules and preference scores. Nevertheless, algorithmic transparency does not establish the validity of the input. The prerequisite relations, cognitive levels, difficulty ratings, and content types were assigned by the researcher. Compliance with these assignments shows that the algorithm followed the encoded design but does not prove that the assignments represent the best pedagogical order.

Difficulty smoothness illustrates the distinction between a preference and a guarantee. The criterion contributes to candidate scoring, but large upward jumps are not explicitly prohibited. Their absence in the default sequence was therefore an observed property of this benchmark rather than a universal guarantee of SMSA.

Weight Sensitivity and Criterion Contributions

The weight-grid analysis indicated that the default sequence was not dependent on a single narrow weight configuration. However, this stability was partly structural because prerequisite and cognitive-stage filtering frequently left only one candidate. The high rank correlations therefore reflect the interaction between the weights and the benchmark graph rather than an inherent insensitivity of the algorithm.

The ablation analysis clarified the roles of the soft criteria. Removing semantic continuity reduced adjacent similarity, while removing content-type diversity increased repetition. Thematic coverage influenced continuity, repetition, and thematic switching simultaneously. Difficulty smoothness did not affect the sequence under the available candidate sets. This does not establish that the criterion is generally unnecessary; its contribution may become visible in larger collections containing greater competition among candidates with different difficulty levels.

The findings also show why the metrics must be interpreted jointly. High semantic continuity can coexist with reversed prerequisite relations, while low content-type repetition can result from frequent but structurally disordered changes. No single metric therefore identifies an educationally preferable pathway. SMSA represents one explicit balance among structural restrictions and descriptive preferences rather than a universally optimal ordering rule.

Implications, Limitations, and Future Research

Recent higher education research demonstrates that short-form social-media content can be deliberately integrated into university learning activities and positively received by learners (Conde-Caballero et al., 2024). The present study addresses a preceding design problem: how multiple objects might be arranged into an explicit pathway before delivery or learner-based evaluation. The procedure may support planned social media series, digital literacy materials, orientation resources, and other compact instructional collections. It may also identify conditions requiring review, such as invalid prerequisite graphs, repeated content types, or abrupt difficulty transitions.

Several limitations constrain these implications. The analysis used one small, researcher-constructed benchmark,

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

and frequent single-candidate steps limited the influence of the soft criteria. Cognitive level, difficulty, content type, and prerequisite relations were assigned rather than independently validated. TF–IDF cosine similarity captured lexical overlap and may overlook conceptual relationships expressed through different vocabulary. Moreover, the structural metrics do not measure comprehension, retention, engagement, cognitive load, or transfer. A sequence designed for social media may also not be experienced as intended because learners can enter midway, skip objects, follow external links, or encounter content through platform ranking.

Future computational evaluation should use larger and independently developed collections across subjects and languages, more varied prerequisite structures, and broader difficulty profiles. Multiple annotators could assess the consistency of metadata and prerequisite assignments, while alternative semantic representations could test dependence on TF–IDF. Following independent content review, learner-based studies would be required to determine whether structurally coherent SMSA pathways improve learning or engagement. Until such evidence is available, SMSA should be regarded as a transparent content-design and diagnostic procedure rather than a validated instructional intervention.

CONCLUSION

This study developed and computationally evaluated SMSA as a transparent procedure for sequencing a fixed collection of social-media-compatible microlearning objects. The algorithm separates eligibility from preference: prerequisite feasibility and cognitive staging restrict the candidate set, while semantic continuity, difficulty smoothness, thematic coverage, and content-type diversity guide selection among eligible objects.

The comparison showed that the sequencing methods emphasized different structural properties. Prerequisite-only sequencing preserved dependencies but not cognitive progression; semantic-only sequencing maximized local textual continuity without preserving prerequisite or cognitive order; and cognitive-only sequencing protected cognitive progression without guaranteeing prerequisite satisfaction. Within the benchmark, SMSA satisfied all specified prerequisites and produced no cognitive regressions or large upward difficulty jumps, although it did not dominate every soft metric. Weight-sensitivity and ablation analyses further showed that the sequence reflected both the graph structure and the contributions of individual preference criteria.

These findings verify the operation of the specified rules within a controlled benchmark; they do not demonstrate improved learning or establish the researcher-defined relations as an optimal curriculum. SMSA's contribution is an inspectable content-design procedure for constructing a common initial pathway when learner data are unavailable. Evaluation with larger, independently reviewed collections and subsequent learner-based research is required before conclusions can be drawn about comprehension, retention, engagement, or transfer.

Data and code availability

The benchmark data, source code, parameter settings, and generated outputs can be provided to the editor and reviewers upon request. Following publication, these materials will be available from the corresponding author upon reasonable request.

Ethical Statement

The study involved no human participants, personal data, identifiable institutions, social media accounts, or observations of user behavior. All objects and metadata were researcher-constructed and all sequences were generated computationally. Ethics committee approval and informed consent were therefore not applicable under the relevant institutional criteria.

Conflict of Interest

The author declares no conflict of interest.

Funding

This research received no specific funding.

REFERENCES

Alias, N. F., & Abdul Razak, R. (2023). Exploring the pedagogical aspects of microlearning in educational settings: A systematic literature review. *Malaysian Journal of Learning and Instruction, 20*(2), 267–294. https://doi.org/10.32890/mjli2023.20.2.3

Aytekin, M. C., & Saygın, Y. (2024). ACE: AI-assisted construction of educational knowledge graphs with prerequisite relations. *Journal of Educational Data Mining, 16*(2), 85–114. https://doi.org/10.5281/zenodo.14250896

Chanaa, A., & El Faddouli, N. (2024). Prerequisites-based course recommendation: Recommending learning objects using concept prerequisites and metadata matching. *Smart Learning Environments, 11*, Article 16. https://doi.org/10.1186/s40561-024-00301-0

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

PERFECT
JOURNAL OF SMART ALGORITHMS

E-ISSN: E-ISSN: 3064-0377
Volume 4, **Number** 1, January 2027
https://doi.org/10.62671/perfect.v4i1.339

Chen, X., Shen, J., Xia, W., Jin, J., Song, Y., Zhang, W., Liu, W., Zhu, M., Tang, R., Dong, K., Xia, D., & Yu, Y. (2023). Set-to-sequence ranking-based concept-aware learning path recommendation. *Proceedings of the AAAI Conference on Artificial Intelligence, 37*(4), 5027–5035. https://doi.org/10.1609/aaai.v37i4.25630

Conde-Caballero, D., Castillo-Sarmiento, C. A., Ballesteros-Yáñez, I., Rivero-Jiménez, B., & Mariano-Juárez, L. (2024). Microlearning through TikTok in higher education: An evaluation of uses and potentials. *Education and Information Technologies, 29*, 2365–2385. https://doi.org/10.1007/s10639-023-11904-4

Denojean-Mairet, M., López-Pernas, S., Agbo, F. J., & Tedre, M. (2024). A literature review on the integration of microlearning and social media. *Smart Learning Environments, 11*, Article 46. https://doi.org/10.1186/s40561-024-00334-5

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y.-S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, Article 100074. https://doi.org/10.1016/j.caeai.2022.100074

Larsen, T. M., Endo, B. H., Yee, A. T., Do, T., & Lo, S. M. (2022). Probing internal assumptions of the revised Bloom's taxonomy. *CBE—Life Sciences Education, 21*(4), Article ar66. https://doi.org/10.1187/cbe.20-08-0170

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., VanderPlas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825–2830. https://www.jmlr.org/papers/v12/pedregosa11a.html

Perez, E., Manca, S., Fernández-Pascual, R., & Mc Guckin, C. (2023). A systematic review of social media as a teaching and learning tool in higher education: A theoretical grounding perspective. *Education and Information Technologies, 28*, 11921–11950. https://doi.org/10.1007/s10639-023-11647-2

Rof, A., Bikfalvi, A., & Marques, P. (2024). Exploring learner satisfaction and the effectiveness of microlearning in higher education. *The Internet and Higher Education, 62*, Article 100952. https://doi.org/10.1016/j.iheduc.2024.100952

Sweller, J. (2024). Cognitive load theory and individual differences. *Learning and Individual Differences, 110*, Article 102423. https://doi.org/10.1016/j.lindif.2024.102423

Takami, K., Flanagan, B., Dai, Y., & Ogata, H. (2023). Personality-based tailored explainable recommendation for trustworthy smart learning system in the age of artificial intelligence. *Smart Learning Environments, 10*, 65. https://doi.org/10.1186/s40561-023-00282-6

Vassoyan, J., Schütt, A., Vie, J. J., Lekshmi-Narayanan, A. B., André, E., & Vayatis, N. (2024). A Pre-trained graph-based model for adaptive sequencing of educational documents. *arXiv preprint arXiv:2411.11520*. https://doi.org/10.48550/arXiv.2411.11520

Zhang, S., Hui, N., Zhai, P., Xu, J., Cao, L., & Wang, Q. (2023). A fine-grained and multi-context-aware learning path recommendation model over knowledge graphs for online learning communities. *Information Processing & Management, 60*(5), 103464. https://doi.org/10.1016/j.ipm.2023.103464

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.