



Fuzzy Kano Validation of Generative AI-Curated Features for Simponia Redesign

Firman Noor Praadita*

Institut Teknologi Sepuluh
Nopember,
Indonesia

Ellya Zulaikha

Institut Teknologi Sepuluh
Nopember,
Indonesia

Sabar

Institut Teknologi Sepuluh
Nopember,
Indonesia

***Corresponding author:**

Firman Noor Praadita, Institut Teknologi
Sepuluh Nopember, Indonesia.

✉ 6032242115@student.its.ac.id

Article Info:

Article history:

Received: July 18, 2026

Revised: September 09, 2026

Accepted: October 05, 2026

Available Online: October 15, 2026

Keywords:

AI-Assisted Design;
Feature Validation;
Fuzzy Kano Model;
Generative AI;
User Experience Design



This is an open access article under the
[CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.

Copyright © 2026 by Author. Published
by Politeknik Siber Cerdika
International

Abstract

Background: Generative AI (Gen AI) has accelerated UX design processes, yet no systematic protocol exists to validate AI-curated features against actual user preferences before prototyping.

Objective: This study applies the Fuzzy Kano Model as a validation checkpoint for Gen AI-curated features in the redesign of Simponia, a web-based portfolio and community management platform at *Universitas Muhammadiyah Malang*.

Methods: An exploratory mixed-methods case design was used. Claude Opus generated 36 feature candidates from a Structured Requirements Document and ISO/IEC 25010 criteria. Fuzzy Kano validation involved 87 Informatics students; fuzzy membership and the Last of Maxima classification method were used to determine Kano categories, while weighted scoring was retained only for post-classification prioritization.

Results: No features were classified as *Must-be* or *One-dimensional* (maximum *Must-be* membership degree = 0.073). Eleven features (30.6%) were classified as *Attractive*, and 25 (69.4%) as *Indifferent*. Triangulation indicated that 58.3% of features were in Quadrant 2, suggesting a misalignment between AI-based technical evaluation and actual user preferences. Sixteen features (44.4%) were flagged as ambiguous ($\Delta\mu < 0.10$).

Conclusion: The Fuzzy Kano Model demonstrates potential as a validation checkpoint by exposing systematic divergence between AI curation and user preferences, with a Quadrant 2 (Q2) rate of 58.3%, indicating the importance of user validation following autonomous AI-assisted feature curation in resource-constrained educational contexts.

To cite this article: Praadita, F. N., Zulaikha, E., & Sabar. (2026). Fuzzy Kano validation of generative AI-curated features for Simponia redesign. *Journal of Business, Social and Technology*, 7(4), 2485–2496. <https://doi.org/10.59261/bustechno.v7i4.799>

INTRODUCTION

The development of Generative AI (Gen AI) over the past decade has fundamentally transformed digital product design practices. Platforms such as ChatGPT, Claude, and Midjourney no longer function merely as passive execution tools but actively participate in creative processes as co-creators (Sreenivasan & Suresh, 2024). In the context of user experience (UX) design, Gen AI demonstrates the ability to automatically generate feature candidates, interface prototypes, and design recommendations in significantly less time than conventional ideation processes (Bilgram & Laarmann, 2023; Girotra et al., 2023; Jo & Lee, 2025). This acceleration positions Gen AI as a relevant instrument for Indonesian educational institutions operating with limited resources, where design process efficiency is a significant constraint (Marthasari et al., 2025; Yang & Wong, 2024). In higher education digital services, however, this efficiency argument must be

balanced against feature relevance. Portfolio and community platforms serve users with different goals, and a technically feasible feature can still provide little perceived value if it does not align with users' academic workflows. Prior work on e-portfolio implementation identifies adoption barriers related to institutional context, user practices, and implementation strategy (Marthasari et al., 2025), while Indonesian UX research also demonstrates the importance of combining structured design methods with direct usability-oriented evaluation (Marthasari et al., 2025). These considerations make pre-prototyping validation particularly relevant when institutions have limited capacity to repeatedly redesign and retest large feature sets.

Nevertheless, the integration of Gen AI into UX design processes presents unresolved challenges in the literature. A systematic review by Stige et al. (2024) of 73 studies on AI in UX design found that existing research tends to focus on specific tools without documenting systematic and replicable protocols. Takafoli et al. (2024), through interview studies with 24 UX practitioners, revealed that Gen AI adoption in industry is still proceeding in an ad hoc manner without standardized validation guidelines. Furthermore, Polster et al. (2024) identified substantive risks in the form of design fixation, namely, the tendency of designers to accept Gen AI output without critical evaluation, potentially resulting in features that are not aligned with actual user needs (Wadinambiarachchi et al., 2024). This risk becomes more significant when Gen AI operates autonomously in feature curation because there is no inherent validation mechanism to ensure that AI-generated output reflects actual user preferences. The Simponia redesign provides a concrete setting for examining this problem. The platform serves a population of 2,190 Informatics students and supports portfolio and community management functions that involve different user roles. Its redesign therefore creates a practical risk: AI-assisted ideation may expand the number of technically plausible features faster than the institution can validate their actual usefulness. In this context, the central problem is not whether Gen AI can generate features, but whether an explicit validation stage can distinguish features that users value from those that are technically reasonable yet perceived as indifferent. Related evidence also indicates that Generative AI can increase individual creative output while reducing collective diversity, reinforcing the need to guard against convergence and fixation in AI-assisted ideation (Doshi & Hauser, 2024; Tholander & Jonsson, 2023).

The Kano Kano et al. (1984) Model and Burgess and Sunmola (2022) provides an established framework for classifying features based on their effects on user satisfaction into Must-be, One-dimensional, Attractive, Indifferent, and Reverse categories. The application of this model in the context of AI-curated features presents measurement and classification challenges because Gen AI output involves inherent uncertainty that cannot be adequately represented by conventional discrete Kano classification approaches (Karakurt & Cebi, 2025). The Fuzzy Kano Model approach developed by Lee and Huang (2009) and Jo and Lee (2025) addresses this limitation by integrating fuzzy logic into the Kano classification procedure, allowing each feature to have degrees of membership across multiple categories simultaneously. Recent applications by Karakurt and Cebi (2025) in mobile application feature design demonstrate the advantages of this method in handling heterogeneous user preferences and producing more granular feature rankings than traditional Kano analysis. In the context of digital services, Cavacece et al. (2024) also demonstrated the effectiveness of the Kano Model in identifying attributes that increase user satisfaction on digital health platforms.

The literature review above identifies three research gaps. First, there is no systematic protocol documenting how Gen AI can be structurally integrated into the UX design ideation and feature curation phases (Stige et al., 2024; Takafoli et al., 2024). Second, there is no proposed validation checkpoint between AI-assisted curation and prototyping stages; consequently, features selected by AI have not been systematically validated against actual user preferences before implementation (Kamnerddee et al., 2024; Polster et al., 2024). Third, the Fuzzy Kano Model has rarely been examined specifically for validating features generated by Gen AI. Existing applications in the literature use features derived from literature reviews or expert interviews rather than from autonomous AI curation (Karakurt & Cebi, 2025; Ren et al., 2025). Accordingly, the novelty claim in this study is framed as a methodological contribution within an underexplored application context rather than as an assertion that no prior application exists.

Based on these gaps, this study proposes a methodological contribution in the form of applying the Fuzzy Kano Model as a validation checkpoint for Gen AI-curated features in UX design

processes. This novelty is methodological: the study positions the Fuzzy Kano Model not as a general prioritization tool but as a mechanism that specifically bridges probabilistic Gen AI output with empirical validation based on user preferences (Lu et al., 2022; Petridis et al., 2024). The application context is the redesign of Simponia, a web-based platform for portfolio and community management for Informatics students at Universitas Muhammadiyah Malang, representing an educational system class with comprehensive reengineering needs and institutional resource constraints. This positioning extends prior applications of the Fuzzy Kano Model by using user-derived fuzzy classification not merely for general feature prioritization but as a gate between autonomous AI curation and subsequent design decisions.

The research questions posed are: How can the Fuzzy Kano Model function as an effective validation checkpoint for Gen AI-curated features in UX design processes, and what Kano category distribution is produced by autonomously Gen AI-curated features? The aim of this study is to evaluate the application of the Fuzzy Kano Model as a validation checkpoint between the Gen AI-assisted feature curation phase and the prototyping phase, while also identifying category distribution patterns that characterize AI-generated features in the context of educational web applications.

METHOD

This research is an exploratory case study employing a mixed-methods approach that focuses on GenAI-assisted feature curation and Fuzzy Kano validation before prototyping. The qualitative component is used to establish initial contextual needs and develop a Structured Requirements Document, while the quantitative component is used to assess user preferences through the Fuzzy Kano Model. The case study object is Simponia, a web-based platform for portfolio and community management for students in the Informatics Study Program at Universitas Muhammadiyah Malang (UMM), with an active user population of 2,190 students. This research focuses on the feature curation and validation stages of the UX design cycle, with the complete protocol, including prototyping and usability evaluation stages, documented in a follow-up study. The research method flow is presented in Figure 1. The qualitative and quantitative components were sequentially connected: stakeholder information was first transformed into the Structured Requirements Document, which was then used as the sole seed input for AI-assisted feature generation, and the resulting locked feature set was subsequently evaluated by users through Fuzzy Kano analysis. This sequence was used to separate AI-based technical curation from user-preference validation.

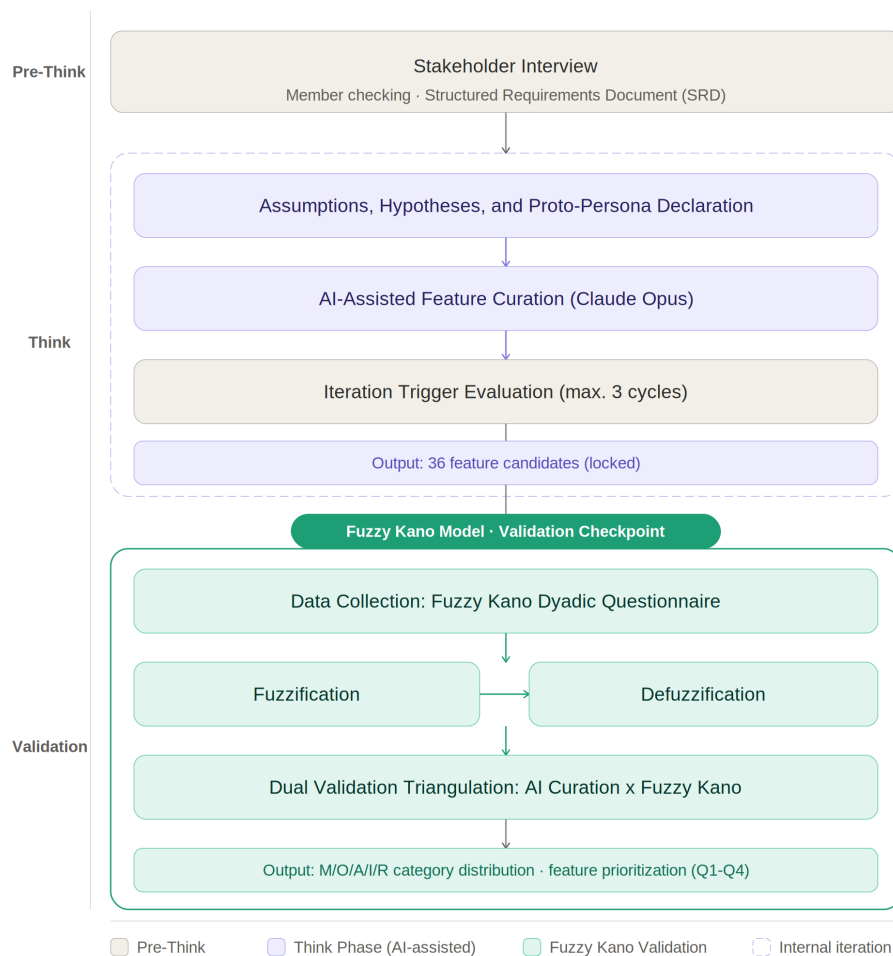


Figure 1. Research method flow: Pre-Think to Fuzzy Kano Model validation

The Pre-Think phase aims to explore stakeholder needs before the AI-assisted generation process begins. Data collection was conducted through semi-structured interviews with one key informant, the manager of the UMM Informatics Laboratory, who has comprehensive knowledge of the needs of students, lecturers, and administrators. The interview results were validated through member checking with the informant and synthesized into a Structured Requirements Document (SRD) encompassing 11 functional requirements categorized according to MoSCoW, nonfunctional requirements based on the ISO/IEC 25010 framework (ISO, 2023; ISO/IEC, 2011), as well as pain points and user stories for each user segment (students, lecturers, and administrators), which served as the sole seed input for the Think phase.

The Think phase used Claude Opus as an agent performing autonomous feature curation based on ISO/IEC 25010 criteria. The process employed single-stage prompting with diversity-prompting mechanisms, including explicit diversity instructions, multi-persona framing, edge-case coverage, layered portfolio and community perspectives, and explicitly communicated technical constraints (Bilgram & Laarmann, 2023; Jo & Lee, 2025). The ISO/IEC 25010 evaluation criteria embedded in the prompt included Functional Suitability, Operability, and Maintainability. The Desirability dimension was deliberately excluded from researcher preference assessment and fully deferred to the Fuzzy Kano validation stage. The output of this phase consisted of 36 feature candidates distributed across six functional clusters, which were declared locked after trigger evaluation showed no activation in the first cycle. For reproducibility, the documented prompt structure consisted of the Structured Requirements Document as the sole content input, explicit instructions to diversify feature candidates across user personas and edge cases, ISO/IEC 25010-based evaluation criteria, and a required feature-priority output. The manuscript records Claude Opus as the model used; because model-build identifiers, access date, and generation parameters were not documented as experimental factors, replication should be interpreted at the procedural rather than bit-for-bit output level. This reporting limitation is acknowledged in

the limitations section.

The Validation phase used the Fuzzy Kano Model following Karakurt and Cebi (2025). The instrument used paired functional and dysfunctional questions for each feature with the conventional five-response Kano format (Like, Must-be, Neutral, Live-with, and Dislike) (Burgess & Sunmola, 2022; Kano et al., 1984). The population comprised 2,190 active Informatics students. A Slovin calculation with a 10% margin of error was used only as an initial recruitment benchmark of 96 participants, not as a justification for probability sampling. Participant selection remained stratified purposive by semester and required prior experience managing academic portfolios. Of the 89 completed questionnaires, two straight-lining responses were excluded, yielding an analytic sample of 87. Because the achieved sample was below the recruitment benchmark and the selection procedure was nonprobabilistic, the findings are interpreted as exploratory and are not claimed to be statistically representative of the full population.

Fuzzy Kano analysis was conducted in two stages. First, fuzzification: each respondent's functional and dysfunctional responses were encoded as five-dimensional one-hot vectors and combined via an outer product to produce a 5×5 relation matrix. The matrices were then aggregated and divided by N to produce membership degrees for each feature, with the membership degrees summing to 1 (Karakurt & Cebi, 2025). Second, defuzzification: the primary category was determined using the Last-of-Maxima (LoM) method, with the hierarchy $M > O > A > I > R$ used for tie handling. Quantitative scores were calculated using a weighted average with weights of $M = 10$, $O = 7$, $A = 4$, $I = 1$, and $R = 0$. Features with a difference of less than 0.10 between the two highest membership degrees were flagged as ambiguous (Karakurt & Cebi, 2025). The Customer Satisfaction Index (CSI) and Customer Dissatisfaction Index (CDI) were calculated using the formulas from Berger et al. (1993) and Gajdošíková et al. (2026) as complementary prioritization metrics. The weighting scheme ($M = 10$, $O = 7$, $A = 4$, $I = 1$, $R = 0$) was used as an ordinal prioritization aid after category membership had been estimated; it did not determine the primary Kano category, which was assigned through Last-of-Maxima. Higher weights therefore reflected the increasing implementation importance associated with Must-be, One-dimensional, and Attractive requirements, whereas Indifferent and Reverse responses received minimal or zero priority weight.

RESULTS AND DISCUSSION

Results

Think Phase: Gen AI-Assisted Feature Curation

The Think phase produced 36 feature candidates through single-stage prompting with Claude Opus using three-dimensional ISO/IEC 25010 evaluation criteria. The feature distribution by cluster and AI ratings are presented in Table 1. In the AI assessment, High Priority denoted features judged to be strongly aligned with the specified ISO/IEC 25010 criteria and SRD needs; Consider denoted plausible but nonessential candidates; and Low Priority denoted features with weaker alignment or lower expected implementation value. These labels represent AI-side technical curation rather than user desirability judgments.

Table 1

Think Phase Output Distribution: 36 Feature Candidates per Cluster

Cluster	No. Features	High Priority	Consider	Low Priority
Portfolio Management	8	5	2	1
Portfolio Discovery	6	4	1	1
Social & Interaction	7	4	3	0
Community Management	6	4	2	0
UX Quality & Performance	5	4	1	0
Profile & Identity	4	1	2	1
Total	36	22 (61.1%)	11 (30.6%)	3 (8.3%)

None of the three iteration triggers were activated, so the Think phase was completed in a single cycle. All 36 features entered the questionnaire without researcher-led preference filtering because the Desirability dimension was deliberately deferred entirely to Fuzzy Kano validation.

Fuzzy Kano Validation: Data Collection

Of the 89 respondents who completed the questionnaire, 2 were excluded because of detected straight-lining response patterns, resulting in a final analytical sample of $n = 87$. Respondents were distributed across semesters 2 to 8: semester 2 (35.6%), semester 4 (13.8%), semester 6 (39.1%), and semester 8 (11.5%). The predominance of semester 6 respondents reflects the characteristics of voluntary participation within the active respondent population.

Calculation Example: F-028 (Modern Design Pattern Consistency)

Table 2 presents the fuzzification and defuzzification process for feature F-028, which had the highest score among the features assigned a definitive (nonambiguous) category.

Table 2

Fuzzy Kano Calculation Example for F-028 (Design Pattern Consistency, $n=87$)

Stage	Parameter	Value
Fuzzification	P(M)	0.00
	P(O)	0.33
	P(A)	0.54
	P(I)	0.12
	P(R)	0.01
	Sum- μ	1.00
Defuzzification (LoM)	Final category	Attractive ($\mu_A = 0.54$)
Quantitative score	Weighted average	4.59 / 10
	CSI	0.88
	CDI	-0.33

The $\mu_A = 0.54$ value far exceeds the membership degrees of the other categories, so the feature is not classified as ambiguous (the difference from $\mu_O = 0.21$ is well above the 0.10 threshold). A CSI of 0.88 indicates a high potential for increasing satisfaction, whereas a CDI of -0.33 indicates a moderate potential for dissatisfaction if the feature is absent (Berger et al., 1993; Karakurt & Cebi, 2025).

Fuzzification and Defuzzification Results: All 36 Features

The final category distribution of all 36 features is presented in Table 3, and the category distribution is visualized in Figure 2.

Table 3

Fuzzy Kano Category Distribution of 36 Feature Candidates

Category	No. Features	Percentage
Must-be (M)	0	0%
One-dimensional (O)	0	0%
Attractive (A)	11	30.6%
Indifferent (I)	25	69.4%
Reverse (R)	0	0%

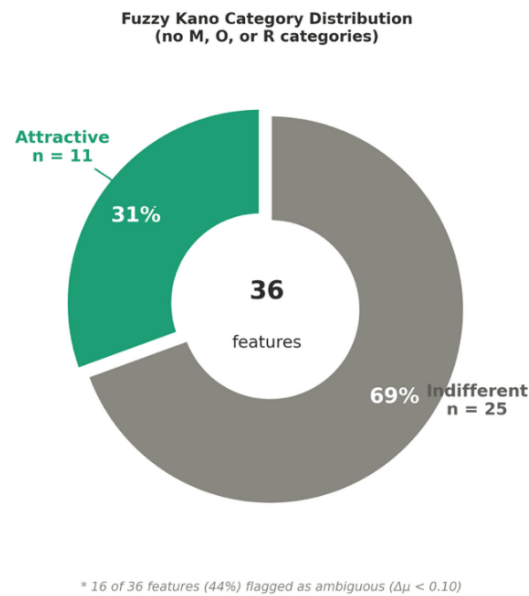


Figure 2. Fuzzy Kano category distribution of 36 feature candidates

The maximum μ_M value across all 36 features was only 0.073, for F-005 (Edit & Version Note). Of the 36 features, 16 (44.4%) were flagged as ambiguous, with a difference of less than 0.10 between the two highest membership degrees. The score ranking of all features is displayed in Figure 3. The dominance of the Indifferent category is interpreted cautiously. The AI curation criteria emphasized technical suitability and system needs, whereas the Kano responses measured satisfaction consequences from the user perspective. The two evaluation logics therefore capture different constructs, which can produce a high proportion of technically plausible features that do not materially increase or decrease user satisfaction. Likewise, the absence of Must-be and One-dimensional classifications is treated as a sample-specific pattern rather than evidence that such requirements cannot exist in other portfolio systems.

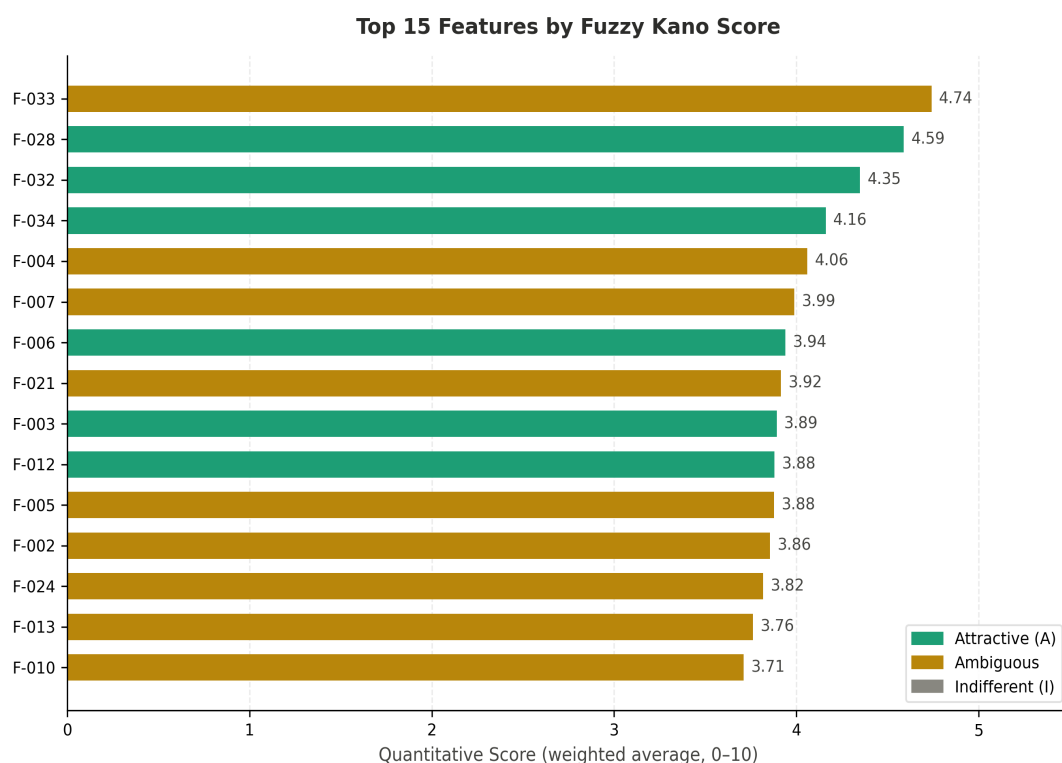


Figure 3. Top 15 features by Fuzzy Kano score

Feature Prioritization: 11 Q1 Features (Implementation)

Features meeting the Q1 criteria (AI = High Priority and Kano = Attractive) are presented in Table 4. Among the 11 features, 5 are ambiguous (F-033, F-004, F-002, F-009, and F-011). These ambiguous features are categorized as Attractive with caution and recommended for micro-validation before full implementation. F-033 illustrates the corrective role of second-stage validation. Although its AI-side rating was Consider rather than High Priority, its fuzzy membership profile was dominated by Attractive/One-dimensional responses, and it achieved the highest weighted score (4.74), with CSI = 0.76 and CDI = -0.39. Thus, the final priority interpretation was not taken directly from the AI label; rather, it incorporated user-derived Kano membership and satisfaction indices, demonstrating how user validation can revise the relative importance implied by AI curation.

Table 4*Q1 Priority Features for Implementation (n=11)*

ID	Feature Name	Cluster	Kano	Score	CSI	CDI	Ambiguous
F-033	Responsive Desktop-First Layout	UX Quality	A/O	4.74	0.76	-0.39	Yes
F-028	Design Pattern Consistency	UX Quality	A	4.59	0.88	-0.33	No
F-032	Single-Page Documentation	UX Quality	A	4.35	0.78	-0.31	No
F-034	Student Profile	Profile	A	4.16	0.76	-0.27	No
F-004	Category & Tag Management	Portfolio Mgmt	A/I	4.06	0.67	-0.32	Yes
F-006	Reorder/Pin Featured Work	Portfolio Mgmt	A	3.94	0.64	-0.25	No
F-003	Draft vs Published State	Portfolio Mgmt	A	3.89	0.69	-0.28	No
F-012	Public Portfolio Page	Discovery	A	3.88	0.72	-0.26	No
F-002	Rich Work Detail	Portfolio Mgmt	A/I	3.86	0.65	-0.28	Yes
F-009	Landing-Page Showcase	Discovery	A/I	3.61	0.62	-0.24	Yes
F-011	Browse/Explore Feed	Discovery	A/I	3.43	0.60	-0.19	Yes

Table 5*Ambiguous Feature Classification and Implementation Implications*

Status	Implementation Implication
Definitive Attractive	Direct implementation priority
Attractive (ambiguous)	Requires micro-validation before full implementation
Definitive Indifferent	Deprioritized — excluded from Design phase
Indifferent (ambiguous)	Requires additional interpretation — candidate for further study

Dual Validation Triangulation: AI Curation versus Fuzzy Kano

Triangulation between the AI curation assessment and Fuzzy Kano results produced the distribution shown in Table 6. The strategic position of each feature on the CSI-CDI matrix is displayed in Figure 4.

Table 6*Dual Validation Triangulation Matrix Distribution*

Quadrant	Description	Count	%
Q1	AI=High, Kano=Attractive: Implementation	11	30.6%
Q2	AI=High, Kano=Indifferent: Divergence Investigation	21	58.3%
Q3	AI=Low, Kano=Attractive: Reconsideration	0	0%
Q4	AI=Low, Kano=Indifferent: Deprioritization	4	11.1%

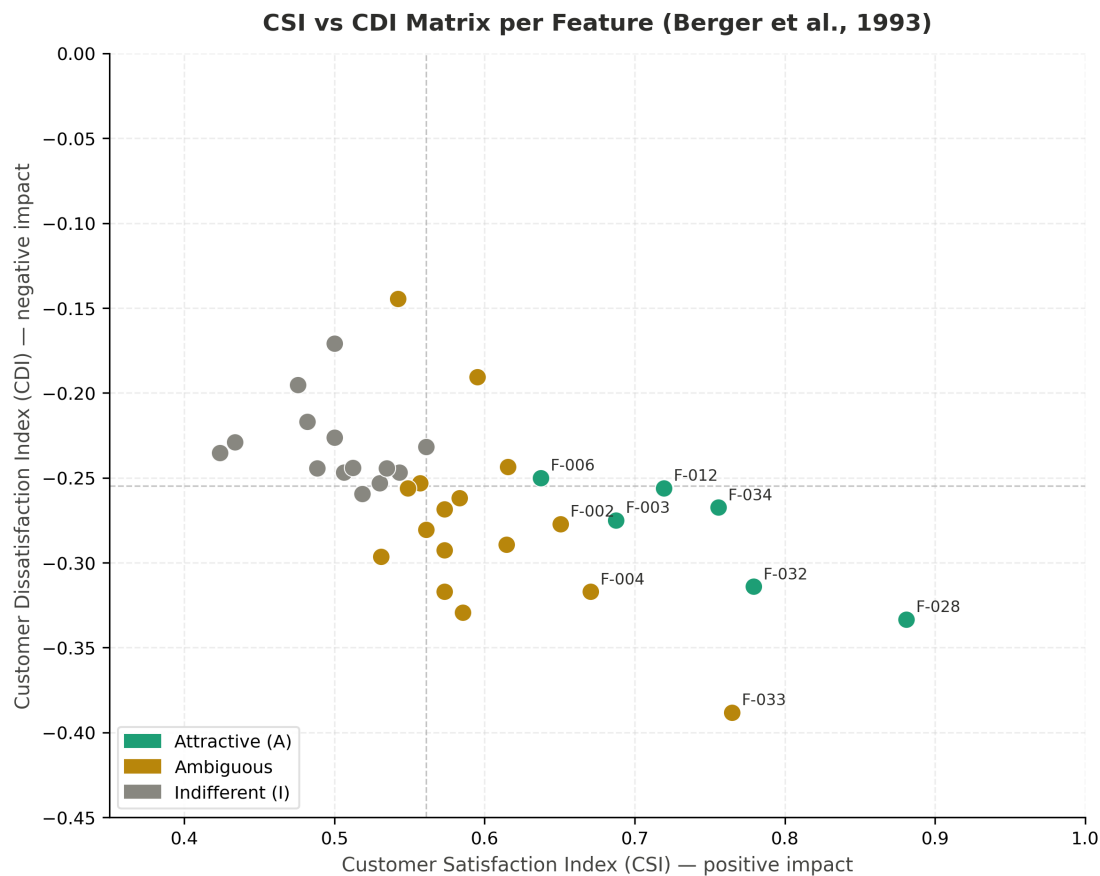


Figure 4. CSI vs CDI matrix per feature Berger et al. (1993) and Gajdošíková et al. (2026)

Table 7

Representative Q2 Features: Divergence Between AI Curation and User Preferences

ID	Feature Name	Reason AI Rated High	Kano Result	Divergence Interpretation
F-007	Activity Notification	Supports community engagement	I	Students do not need push notifications for portfolio platforms
F-021	Comments & Discussion	Encourages community interaction	I	Social interaction not perceived as core portfolio need
F-005	Edit & Version Note	Supports work history tracking	I (amb)	Versioning perceived as overhead, not added value
F-024	Portfolio Analytics	Supports decision making	I (amb)	Analytics not relevant for basic showcase needs
F-013	Search & Filter	Enables content discovery	I (amb)	Discovery more relevant for admin than individual users
F-010	Achievement Badge	Gamifies engagement	I (amb)	Badges not perceived as meaningful added value
F-008	Collaboration Space	Supports teamwork	I	Collaboration not a priority for individual portfolio context
F-017	Event & Workshop Feed	Community activity info	I	Feed perceived as duplicate of existing information channels

Discussion

Three main findings are discussed analytically. First, the absence-of-M finding: the absence of Must-be category features across all 36 features indicates Simponia's characteristic as a discretionary platform within the academic ecosystem. Students view Simponia as an additional

tool rather than a mandatory platform within this respondent group. This interpretation is limited to the observed Kano response pattern and should not be read as evidence about all institutional users or historical system acceptance. The dominance of Indifferent (69.4%) indicates that most AI-curated features are assessed neutrally from a satisfaction-dissatisfaction perspective. An alternative interpretation (that the Must-be response option felt too strong linguistically for some respondents) cannot be ruled out and is documented as an interpretive limitation. The practical implication is that Simponia's design should focus on experiences that provide delight through Attractive features rather than merely meeting basic expectations. Conceptually, this finding suggests that technical functionality and satisfaction-critical requirements are not equivalent. Features may support portfolio administration while still being experienced as optional by students. The implication is that the redesign should distinguish baseline system requirements established by institutional stakeholders from delight-oriented attributes identified through student preference data.

Second, the 58.3% Q2 rate is the most significant empirical contribution of this study. More than half of the features deemed feasible by Generative AI based on ISO/IEC 25010 were not aligned with actual user preferences. This finding supports the importance of the validation checkpoint identified by Polster et al. (2024) and Takafoli et al. (2024): AI curation without a validation checkpoint carries a risk of producing technically feasible but user-irrelevant features. The F-033 case reinforces this finding: a feature rated Consider by AI actually obtained the highest Fuzzy Kano score (4.74), demonstrating that Fuzzy Kano can function as a correction mechanism for technical bias in AI curation. This aligns with the arguments of Duan et al. (2024) and Lu et al. (2022) that AI integration in UX design requires human validation mechanisms as a counterbalance. Operationally, Q2 contains 21 of the 36 features that received a High Priority AI assessment but were classified as Indifferent by users. It is termed divergence because the AI-side technical prioritization and the user-side satisfaction classification point in different implementation directions. The pattern therefore provides empirical evidence supporting the need for a user-validation step after AI curation, without establishing that this checkpoint is superior to alternative validation methods.

Third, the 44.4% ambiguity rate indicates that student preferences toward Web-based portfolio features are not uniformly distributed. Fuzzy Kano provides more granular information than conventional Kano because it does not force a single category onto features with dispersed preference distributions. This advantage is consistent with Karakurt and Cebi (2025) argument that fuzzy logic is essential when user populations are heterogeneous. Among the 11 Q1 features, 5 are ambiguous and are recommended for micro-validation before full implementation to reduce the risk of misaligned design. The ambiguity rate may reflect several nonexclusive mechanisms: heterogeneity across semester groups, feature-specific uncertainty, the wording of paired Kano questions, the achieved sample size, and sensitivity to the researcher-defined $\Delta\mu < 0.10$ threshold. Because the present design does not isolate these sources, ambiguity should be interpreted as an indicator of unstable category dominance rather than as direct evidence of user heterogeneity. This is why ambiguous Attractive features are recommended for micro-validation before implementation.

Several limitations should be considered. First, this is a single-case investigation of Simponia, so transferability to other systems requires replication. Second, only Claude Opus was used for AI-assisted curation; other models may generate different feature sets and divergence patterns, and model build/access metadata were not treated as experimental factors. Third, user validation involved students only, without lecturers or administrators. Fourth, the final analytical sample was 87 compared with the recruitment benchmark of 96; the nonprobability sampling design and shortfall limit population-level inference. Fifth, the $\Delta\mu < 0.10$ ambiguity rule was a researcher-defined threshold adopted for this analysis and has not been validated across contexts. These limitations motivate sensitivity testing, multi-model replication, and validation with broader user groups.

CONCLUSION

This exploratory case study demonstrates the potential of the Fuzzy Kano Model as a validation mechanism between AI-assisted feature curation and prototyping. User validation produced a strong concentration of Indifferent features and no dominant Must-be or One-

dimensional classifications, indicating that technically curated features do not automatically translate into satisfaction-relevant requirements in the Simponia context.

The principal empirical contribution is the 58.3% Q2 divergence rate, representing features prioritized highly by the AI process but classified as Indifferent by users. This pattern suggests that a user-preference checkpoint can reveal mismatches that would remain hidden if implementation decisions relied only on AI-assisted technical curation. The result supports the use of human validation as a safeguard while stopping short of claiming comparative effectiveness against other validation approaches.

This study contributes to the Fuzzy Kano literature by documenting its application in an underexplored context: the validation of features autonomously curated by Generative AI. The observed ambiguity patterns also demonstrate the value of retaining fuzzy membership information when category dominance is weak. Future research should test methodological sensitivity to ambiguity thresholds and sample composition, compare outputs from different Generative AI models and feature-generation sources, include lecturers and administrators, and extend the protocol through prototyping and usability evaluation.

ACKNOWLEDGEMENT

The authors acknowledge the Informatics Laboratory of Universitas Muhammadiyah Malang for facilitating access to the Simponia system and supporting the data-collection process. The authors also thank the participating students of the Informatics Study Program for their contribution to the user-validation stage.

AUTHOR CONTRIBUTION STATEMENT

Noor Praadita: Conceptualization, Investigation, Data Curation, Formal Analysis, Writing - Original Draft. Ellya Zulaikha: Supervision, Methodology, Validation, Writing - Review & Editing. Sabar: Supervision, Validation, Technology Management Context, Writing - Review & Editing.

REFERENCES

- Berger, C., Blauth, R., Boger, D., Bolster, C., Burchill, G., DuMouchel, W., Pouliot, F., Richter, R., Rubinoff, A., Shen, D., Timko, M., & Walden, D. (1993). Kano's methods for understanding customer-defined quality. *Center for Quality Management Journal*, 2(4), 3–36.
- Bilgram, V., & Laarmann, F. (2023). Accelerating Innovation With Generative AI: AI-Augmented Digital Prototyping and Innovation Methods. *IEEE Engineering Management Review*, 51(2), 18–25. <https://doi.org/10.1109/EMR.2023.3272799>
- Burgess, P. R., & Sunmola, F. T. (2022). Exploring Attractive Quality Requirements for Short Food Supply Chain Digital Platforms. *International Journal of Information Systems and Supply Chain Management*, 15(1). <https://doi.org/10.4018/ijisscm.304372>
- Cavacece, Y., Maggiore, G., Resciniti, R., & Moretta Tartaglione, A. (2024). Evaluating digital health attributes for users' satisfaction: an application of the Kano model. *The TQM Journal*, 37(3), 831–852. <https://doi.org/10.1108/TQM-09-2023-0301>
- Doshi, A. R., & Hauser, O. P. (2024). Generative AI enhances individual creativity but reduces the collective diversity of novel content. *Science Advances*, 10(28), eadn5290. <https://doi.org/10.1126/sciadv.adn5290>
- Duan, P., Warner, J., Li, Y., & Hartmann, B. (2024). Generating Automatic Feedback on UI Mockups with Large Language Models. *Proceedings of the CHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/3613904.3642782>
- Gajdošíková, Z., Kmeco, L., Hamarneh, I., & Klímová, M. (2026). Is Kano's Model Outdated or Still Essential for Understanding Customer Needs in an Era of Unlimited Choice? *Tourism and Management Studies*, 22(1). <https://doi.org/10.18089/tms.20260102>
- Girotra, K., Meincke, L., Terwiesch, C., & Ulrich, K. T. (2023). *Ideas are Dimes a Dozen: Large Language Models for Idea Generation in Innovation*. The Wharton School Research Paper. <https://doi.org/10.2139/ssrn.4526071>
- ISO. (2023). Systems and software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Product quality model. <https://www.iso.org/Standard/78176.html>, 2023.
- ISO/IEC. (2011). *ISO/IEC 25010:2011 Systems and software engineering - Systems and software*

- Quality Requirements and Evaluation (SQuaRE) - System and software quality models.* International Organization for Standardization.
- Jo, S., & Lee, G. (2025). A Comparative Study of Design Ideation between Generative AI and Product Designers: Creativity, Innovation, and Empathy. *Archives of Design Research*, 38(2), 485–502. <https://doi.org/10.15187/adr.2025.05.38.2.485>
- Kammerddee, C., Putjorn, P., & Intarasirisawat, J. (2024). AI-Driven Design Thinking: A Comparative Study of Human-Created and AI-Generated UI Prototypes for Mobile Applications. *8th International Conference on Information Technology 2024, InCIT 2024*, 237–242. <https://doi.org/10.1109/INCIT63192.2024.10810565>
- Kano, N., Seraku, N., Takahashi, F., & Tsuji, S. (1984). Attractive Quality and Must-Be Quality. *Journal of the Japanese Society for Quality Control*, 14(2), 39–48.
- Karakurt, N. F., & Cebi, S. (2025). A fuzzy Kano model proposal for sustainable product design: Mobile application feature analysis. *Applied Soft Computing*, 172. <https://doi.org/10.1016/j.asoc.2025.112824>
- Lee, Y. C., & Huang, S. Y. (2009). A new fuzzy concept approach for Kano's model. *Expert Systems with Applications*, 36(3), 4479–4484. <https://doi.org/10.1016/j.eswa.2008.05.034>
- Lu, Y., Zhang, C., Zhang, I., & Li, T. J. J. (2022). Bridging the Gap Between UX Practitioners' Work Practices and AI-Enabled Design Support Tools. *Proceedings of the CHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/3491101.3519809>
- Marthasari, G., Noor Praadita, F., & Seto Wiyono, B. (2025). Aplikasi Metode Lean User Experience dan System Usability Scale pada Analisis, Perancangan, dan Evaluasi Antarmuka Aplikasi Mobile. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, 12(2), 263–274. <https://doi.org/10.25126/jtiik2025125762>
- Petridis, S., Terry, M., & Cai, C. J. (2024). PromptInfuser: How Tightly Coupling AI and UI Design Impacts Designers' Workflows. *Proceedings of the 2024 ACM Designing Interactive Systems Conference, DIS 2024*, 743–756. <https://doi.org/10.1145/3643834.3661613>
- Polster, L., Bilgram, V., & Gortz, S. (2024). AI-Augmented Design Thinking: Potentials, Challenges, and Mitigation Strategies of Integrating Artificial Intelligence in Human-Centered Innovation Processes. *IEEE Engineering Management Review*. <https://doi.org/10.1109/EMR.2024.3512866>
- Ren, J., Chin, J. F., & Mansor, M. S. B. A. (2025). Sustainable product design based on fuzzy Kano, QFD, and TRIZ. *Journal of Engineering Research*. <https://doi.org/10.1016/j.jer.2025.10.004>
- Sreenivasan, A., & Suresh, M. (2024). Design thinking and artificial intelligence: A systematic literature review exploring synergies. *International Journal of Innovation Studies*, 8(3), 297–312. <https://doi.org/10.1016/j.ijis.2024.05.001>
- Stige, A., Zamani, E. D., Mikalef, P., & Zhu, Y. (2024). Artificial intelligence (AI) for user experience (UX) design: a systematic literature review and future research agenda. *Information Technology and People*, 37(6), 2324–2352. <https://doi.org/10.1108/ITP-07-2022-0519>
- Takafoli, M., Li, S., & Makela, V. (2024). Generative AI in User Experience Design and Research: How Do UX Practitioners, Teams, and Companies Use GenAI in Industry? *Proceedings of the 2024 ACM Designing Interactive Systems Conference, DIS 2024*, 1579–1593. <https://doi.org/10.1145/3643834.3660720>
- Tholander, J., & Jonsson, M. (2023). Design Ideation with AI - Sketching, Thinking and Talking with Generative Machine Learning Models. *Proceedings of the 2023 ACM Designing Interactive Systems Conference, DIS 2023*, 1930–1940. <https://doi.org/10.1145/3563657.3596014>
- Wadinambiarachchi, S., Kelly, R. M., Pareek, S., Zhou, Q., & Velloso, E. (2024). The Effects of Generative AI on Design Fixation and Divergent Thinking. *Proceedings of the CHI Conference on Human Factors in Computing Systems*. <https://doi.org/10.1145/3613904.3642919>
- Yang, H., & Wong, R. (2024). An In-Depth Literature Review of E-Portfolio Implementation in Higher Education: Steps, Barriers, and Strategies. *Issues and Trends in Learning Technologies*, 12(1), 65–101. <https://doi.org/10.2458/itlt.5809>