



BETWEEN TECHNICAL RATIONALITY AND RELATIONAL LABOR: A TECHNOFEMINIST ANALYSIS OF PRESERVICE PRESCHOOL TEACHERS' AI PERCEPTIONS AND METAPHORS

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Abstract:

Artificial intelligence (AI) threatens to undermine teaching by simplifying practices into a rationalized process and potentially causing deskilling. This study investigated preservice preschool teachers' professional perspectives and metaphorical conceptualization of AI within a technofeminist framework. The study focused on the inherent tension between the relational nature of early childhood education and the technical rationality of AI. A convergent parallel mixed-methods design was employed with 150 preservice preschool teachers at a Turkish state university. Data were collected utilizing a 15-item AI perception scale, a metaphor form, and three open-ended questions probing the uses of AI, collaboration with AI systems, and broader anxieties. Findings indicated that despite preservice teachers holding a high awareness of the instructional advantages of AI, their moral reservations persisted independently of pedagogical assessments and showed no correlation with frequency of application. Qualitatively, preservice teachers framed AI through theory-driven themes such as "*the God trick*" and "*deskilling*". Female participants' exclusive articulation of the "*domestication*" theme illustrated a strategy where women tailor technology to their pedagogical goals through relational metaphors such as "*mother*" and "*confidant*." The study demonstrated that AI is not a neutral tool in education but is actively shaped by societal gender structures, necessitating a politically informed approach to teacher education.

Keywords: artificial intelligence in education, technofeminism, preservice preschool teachers, relational labor, deskilling, metaphorical conceptualization

1. Introduction

Artificial intelligence (AI) has penetrated everyday life not only as a technical breakthrough but also as a sociotechnical system that modifies the ways we access

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information, reorganizes business operations and even reshapes educational settings (Whittaker *et al.*, 2018; Williamson *et al.*, 2023). Far from being an exceptional device, it is increasingly becoming an indispensable infrastructure component within educational contexts (Facer & Selwyn, 2021). Although this integration process might be presented as neutral technical advancement, at its core it carries the risk of transforming teaching into a rationalized practice with only standardized and measurable outcomes (Holmes *et al.*, 2019). The rapid adoption of generative AI tools by students, teachers and preservice teachers demonstrates that technologies are no longer mere auxiliary platforms outside the educational setting but have become integral actors within the process of teaching and learning (Akinwalere & Ivanov, 2022; Bearman *et al.*, 2023; Martinez, 2026).

However, this rapid integration raises a fundamental question about how such technologies are perceived and positioned. AI is often perceived in the literature as a relatively neutral and instrumental technology, with a focus on its promises of efficiency, speed, personalization and accessibility (Kaniwa & Adekanmbi, 2026; Ribeiro, 2016; Selwyn, 2017). This prevailing perspective frequently neglects the ways in which technology highlights or obscures certain forms of labor, legitimizes knowledge regimes, and circulates various gender scripts (Wajcman, 2006; Wajcman *et al.*, 2020). The critical literature on educational technology approaches this instrumental optimism with greater caution, indicating that technology not only generates pedagogical benefits but also reflects institutional priorities, inequalities, and specific visions of the future (Bayne, 2015; Selwyn, 2022). For instance, Bayne (2015) argues that the portrayal of technology-enhanced learning is commonly framed within a “smooth” progression; however, educational technologies are not independent of material, political and cultural contexts. Facer and Selwyn’s (2021) proposition of “non-stupid optimism” is crucial at this point: technology should neither be romanticized nor absolutized in a deterministic fashion. Therefore, the ways in which preservice teachers filter these technologies through ethical, pedagogical, and professional criteria are not just a technical adaptation but also a sociotechnical problem with political implications (Bayne, 2015; Selwyn, 2022).

This sociotechnical problem is especially evident in fields where the relational dimension of pedagogy is fundamental. Early childhood education is more than just a field focused on cognitive content delivery; it is, in fact, a relational pedagogical structure that is built upon care, emotional labor, intuitive observation, physical support and trust dynamics (Aktaş, 2026; Noddings, 2013). Noddings’s care ethics and Gilligan’s (1993) relational ethical perspective reveal that decision-making in education and pedagogical accountability are molded by relationships, contexts and reciprocity rather than abstract rules. This perspective suggests that individuals develop through these social relationships. Thus, the entry of AI into the realm of early childhood education is not just a matter of content generation or the ease of planning activities; it fundamentally challenges us to reconsider how caregiving, intuitive teaching and the dynamic relationship with children are conceptualized (Aktaş, 2026; Kalaba Yıldırım & Önder, 2025).

These challenges become particularly acute when they translate into concrete risks to the profession. Research suggests that AI presents significant potential in the design of activities for preschool education, personalized aid, and assisting teachers (Aktaş, 2026; Gölbaşı & Okul, 2024; Güven *et al.*, 2024; Küçükkara *et al.*, 2024). Yet, in light of these technological promises, two fundamental risks arise that jeopardize the ontological foundations of the profession. The first risk is the redefinition of the comprehensive preparation, observation, and pedagogical decision-making of teaching as “*automatable tasks*”, thereby initiating a “*deskilling*” process that dismantles professional expertise (Bearman *et al.*, 2023; Demirdiş, 2026; Aktaş, 2026; Facer & Selwyn, 2021; Kalaba Yıldırım & Önder, 2025). The second risk is the erosion of the worth of care and emotional labor, which are rendered invisible and undervalued within the technical rationality and efficiency narrative that AI imposes (Aktaş, 2026; Kalaba Yıldırım & Önder, 2025; Wajcman, 2020). The logic of “*speed*” in digital capitalism endangers the “*relational time*” of early childhood education, a time that is neither accelerated nor amenable to algorithmic representation (Aktaş, 2026; Wajcman, 2020). Emotional sensitivity and immediate pedagogical intuition are the foundations of relational labor. The overuse of AI may undermine the professional autonomy of preservice preschool teachers and trigger deskilling (Bearman *et al.*, 2023; Facer & Selwyn, 2021).

2. Theoretical Framework

Technofeminism examines the reciprocal nature of technology and gender by arguing that technological change may both reproduce and transform gender inequalities. Wajcman (1991, 2004) argues that technology is socially constructed and gender relations are intrinsic to technological design, use, and representation. Situated within the framework of Feminist Science and Technology Studies (Feminist STS), technofeminism demonstrates that technology is inherently value-laden, permeated by asymmetrical power structures including gender, class, and race (Haraway, 1991; Faulkner, 2001). Accordingly, technology functions not as a mere instrument, but rather as a site of social production wherein relations and identities are generated.

The framework adopted in this study rests upon five essential analytical dimensions. The principle of mutual constitution holds that technology and gender reciprocally shape each other (Wajcman, 2004). Gender relations shape technological development substantially, as technology influences gender relations. In other words, the ways in which preservice preschool teachers perceive AI can shape both its development and its positioning within educational contexts. The concept of gendered scripts refers to gender assumptions embedded in technological design (Wajcman, 2010). Technologies are designed by anticipating specific user profiles, and these predictions often reflect gender norms. In this context, AI applications in early childhood education may involve specific roles for female teachers. The concept of domestication describes the process by which technologies become incorporated into everyday and occupational contexts

(Wajcman, 2004). Users accommodate technologies to their own values, and how teacher candidates conceptualize AI through metaphors is an important indicator of this process.

Technofeminist agency, as conceptualized by Wajcman (2007), argues that women function as dynamic agents and catalysts rather than passive consumers of technology. This perspective illuminates teacher candidates' critical attitudes, resistance, and alternative usage strategies. The concept of material-semiotic patterns implies that the material and semantic dimensions of technologies are intertwined (Haraway, 1991; Wajcman, 2004). AI, functioning simultaneously as technological infrastructure and cultural artifact, perpetuates gender relations across both material and discursive registers. Wajcman (2007) notes that feminist inquiry into technology has evolved from an examination of women's technological access to a more profound interrogation of how gender relations inherently constitute technological systems themselves. This paradigm shift enables an analysis of gendered dynamics across the entire spectrum, ranging from technological design to user engagement.

The adoption of this framework provides a critical basis for analyzing preservice preschool teachers' perceptions and metaphors about AI from a gender perspective. Early childhood education, as a female-dominated profession centered on care labor and relational practices, is loaded with gender codes. The introduction of AI into this field is therefore not a neutral technical issue but a political process intertwined with gender, care work, and professional identities, making visible the power relations behind these perceptions (Cockburn & Ormrod, 1993; Oudshoorn *et al.*, 2004). Hence, the integration of AI is not merely a technical issue, but a political process connected to gendered care work and how professionals perceive themselves. These dynamics illuminate the power relations that shape these conceptualizations (Cockburn & Ormrod, 1993; Oudshoorn *et al.*, 2004).

Existing literature addresses the incorporation of AI into educational contexts across technical, pedagogical, and ethical dimensions. However, it provides insufficient insight into the extent to which gender dynamics influence this integration process. Within female-dominated professional domains centered on care provision, particularly early childhood education, the analysis of preservice teachers' perspectives on AI utilizing a technofeminist framework has been substantially overlooked. Gender-neutral studies investigate technology usage without connecting gender norms, professional feminization, and care labor dimensions. Wajcman (2004) argued that technology is fundamentally intertwined with gendered structures. However, the application of this framework to preservice preschool teachers' AI conceptualizations and their metaphorical representations constitutes a significant research gap. The five analytical dimensions of the technofeminist framework (mutual constitution, gendered scripts, domestication, technofeminist agency, and material-semiotic patterns) provide a useful way to understand different perspectives on artificial intelligence.

The purpose of this study is to elucidate the complex dynamics involving technology, gender, and care work in early childhood educational settings. To investigate how preservice preschool teachers understand and talk about AI, a technofeminist

theoretical perspective is utilized. To this end, the following main research questions and related questions were formulated:

- What are the professional perceptions of artificial intelligence and its metaphorical conceptualizations among preservice preschool teachers, from a technofeminist perspective?

2.1 Sub-Questions

2.1.1 Quantitative Sub-Questions

- 1) What are the levels of preservice preschool teachers' perceptions regarding AI in teaching, learning, and ethics?
- 2) Do these perception levels differ significantly according to demographic variables (age, grade level, technology use frequency, etc.)?

2.1.2 Qualitative Sub-Questions

- 3) What metaphors do preservice preschool teachers use to conceptualize artificial intelligence?
- 4) How do these metaphors cluster around the core dimensions of technofeminism (mutual shaping, gendered scripts, domestication, technofeminist agency, material-semiotic patterns)?
- 5) How do the metaphorical meanings relate to the construction of female teacher identity and professional practices?

2.1.3 Mixed-Methods Integration Sub-Question

- 6) How do the quantitative perception levels and qualitative metaphor themes converge or diverge in offering a technofeminist reading of AI among preservice preschool teachers?

3. Material and Methods

3.1 Research Design

To investigate the preservice preschool teachers' perception of artificial intelligence (AI), their metaphorical framings and the connections between these representations and technofeminist theory, a convergent parallel mixed-methods design was employed through the concurrent collection of quantitative and qualitative data. Within this methodological framework, both datasets were subjected to independent analysis, which were merged for comparative evaluation purposes. According to Creswell (2014, 2022), this approach allows researchers to compare the results to determine whether the results converge, diverge, or complement each other. Consequently, this approach sheds light on both statistical patterns and qualitative meanings pertaining to the same matter. This integrated analysis of two data modalities yields a more holistic understanding of the research problem (Creswell, 2014, 2022). In the present study, integration occurred at the interpretation stage. The quantitative and qualitative findings were analyzed

independently at first, and only later placed together in a joint display matrix to reveal convergence, divergence, and complementarity. The primary rationale behind the adoption of this design is that the research questions of the current study elicit both descriptive and generalizable as well as interpretative and profound responses.

3.2 Participants

The research sample included 150 preservice preschool teachers enrolled in a state university (124 female, 26 male; M age = 20.9 years). The total population of the participating teacher education program consisted of 250 enrolled students; after removing duplicate records, 244 unique students were identified. Of these, 150 volunteered to participate, yielding a response rate of 61.5%. Convenience sampling was utilized for the collection of data. Convenience sampling was chosen for practical accessibility and theoretical appropriateness. Convenience sampling is a widespread strategy in mixed-methods research, since researchers can access participants directly and efficiently (Creswell & Plano Clark, 2018). The predominantly female demographic composition of early childhood teacher education programs provides a context for analyzing how AI is conceptualized and framed in a gendered context from a technofeminist perspective.

Participation in this study was voluntary. As the participants were the researcher's students, the data collection procedure was conducted separately from the course evaluation systems. Additionally, the researcher distinctly informed the participants that they would experience no consequences, including no impact on their grades. Participants were provided with an informed consent form electronically via Google Forms. The form outlined the purpose of the study and the procedures for data collection and maintaining confidentiality. Participants were verbally informed of their right to withdraw from the study at any time without penalty. Although no identifiable risks were present for participants, participants were informed of their right to decline to answer any questions that generated discomfort. This provision was particularly relevant given that the metaphorical form and open-ended questions could elicit personal narratives. After reading and understanding the form, participants provided electronic informed consent by selecting the "*Yes, I approve*" option. Participants who approved the informed consent document completed the AI perception scale, the metaphor form, and the open-ended questions through Google Forms.

The participants were assigned a number to ensure confidentiality; email addresses were not collected via Google Forms, and only anonymous responses were accepted. The data were stored in an encrypted digital environment accessible only to the researcher.

The study was approved by the Social Sciences Ethics Committee of Amasya University (Decision No: 11209, dated 09.03.2026). The research was conducted in accordance with ethical guidelines.

3.3 Data Collection Instruments

3.3.1 Quantitative Component: Artificial Intelligence Perception Instrument

Quantitative data were collected utilizing the Scale of Perceptions Regarding the Use of Artificial Intelligence in Education, developed by Üzümlü *et al.* (2025) and made available via open access through Türkiye Assessment Tools Index. The instrument comprises 15 items organized into three subscales: teaching perception, learning perception, and ethical perception. The original scale development study was conducted in two phases during the 2023–2024 academic year with 597 teachers who reported using various artificial intelligence applications. In the first phase ($n = 424$), exploratory factor analysis was performed; it was found that the three-factor structure explained 57.8% of the total variance. In the second phase ($n = 173$), confirmatory factor analysis confirmed that the final scale, consisting of 15 items and three dimensions, was consistent with the data. The Cronbach's alpha coefficient of internal consistency for the entire scale was determined to be .87; for teaching perception, .79; for learning perception, .82; and for ethical perception, .79. These values demonstrate that the scale constitutes a valid and reliable measurement instrument (Üzümlü *et al.*, 2025).

3.3.2 Qualitative Component: Metaphorical Methodology and Open-Ended Exploration

Qualitative data were collected using two tools. Initially, for the metaphorical framework, the participants completed a prompt sentence: "*Artificial intelligence is like ... because ...*". Afterward, the participants responded to three open-ended questions: (a) on areas of AI usage, (b) on their interaction with AI, (c) their general thoughts about AI.

The notion that metaphors reveal individuals' tacit knowledge, values, and motivations concerning intricate phenomena is grounded in Lakoff and Johnson's (1980) conceptual metaphor theory. This theory suggests human cognition is fundamentally metaphorical in nature. Metaphors function as a bridge between abstract concepts and lived experiences. Schmitt (2005) adapted this theory into a qualitative research methodology, establishing systematic metaphor analysis as a rigorous analytical approach. This analysis has become a widely utilized tool for understanding diverse social phenomena, including educational settings (Malvini Redden, 2017). The metaphorical form employed in this study enabled the researcher to examine the ways in which preservice preschool teachers conceptualize AI and to reveal the ideological and emotional inclinations from a technofeminist perspective.

Open-ended questions enable researchers to gain insight into participants' perspectives without the constraints of predetermined categorical systems and theoretical expectations (Patton, 2002). These three open-ended questions were deliberately designed to illuminate preservice preschool teachers' standpoints, rationales, and ethical accountability regarding AI.

3.4 Data Analysis

3.4.1 Quantitative Analysis

Quantitative data were analyzed through statistical procedures utilizing IBM SPSS Statistics. Frequency distributions and percentage values were calculated to depict the participants' demographic profile. Descriptive statistical parameters (M , SD , range, skewness, kurtosis) for the scale variables were examined; the scale's internal consistency reliability was evaluated through Cronbach's alpha (Field, 2018). The Kolmogorov-Smirnov test revealed non-normal data distribution ($p < .05$). Thus, nonparametric statistical approaches were applied for comparative analyses between groups (Field, 2018). The differences between the two independent groups were examined with the Mann-Whitney U test (gender, AI training status), and the differences between three or more independent groups were examined with the Kruskal-Wallis H test (grade level, AI usage frequency). When a significant difference was found in the Kruskal-Wallis test result ($p < .05$), Tamhane's T2 post-hoc test was used, which relaxes the assumption of variance homogeneity (Field, 2018). Effect sizes were calculated: $r = Z/\sqrt{N}$ for Mann-Whitney U; η^2 for Kruskal-Wallis (Cohen, 1988).

Finally, since the normal distribution assumption was not provided, the relationships between the variables were examined with the Spearman's rank-order correlation; and the relationships between categorical variables were examined with Pearson's chi-square test of independence (Field, 2018). The statistical significance level was determined as $p < .05$.

3.4.2 Qualitative Analysis

Qualitative data were collected from two tools: (i) a metaphor prompt ("Artificial intelligence is like ... because ...") and (ii) three open-ended questions. A deductive thematic analysis based on Wajcman's technofeminist theory was applied to the data obtained from both tools. The analysis process was conducted in three stages:

a. Development of a Codebook

Following the data collection, a codebook was developed from Wajcman's (1991, 2004, 2007, 2010, 2015, 2017, 2023) works related to technofeminist theory. Although codebooks may be developed either before or after data collection, the critical consideration is systematic and transparent coding (Braun & Clarke, 2006; Saldaña, 2021). The codebook consists of a total of 7 main themes and 20 subcodes: (1) Mutual Shaping; (2) Male Culture and Expertise; (3) Labor and Material Conditions; (4) Algorithmic Bias and Data Politics; (5) Space and Digital Space; (6) Relational Labor and Identity in Education; (7) The Gender Politics of Time. The codebook was collaboratively examined by two coders. The operational clarity of the codes was verified by joint coding of both datasets.

b. Unit of Analysis

The metaphor format is a data collection tool that evidently bears the mental images participants apply to conceptualize AI. Participants completed a template "*Artificial*

intelligence is like ... because" The metaphorical statements generated by the participants were taken directly as the unit of analysis. As for the three open-ended questions, the entire response to each question was taken into consideration as a coding unit. This "*holistic coding*" method suggested by Saldaña (2021) entails assigning a single code to large data units and interpreting the data. In the current study, treating each answer as a unified unit prevented the fragmentation of meaning from its context and guaranteed that coding was conducted utilizing a holistic approach. Responses lacking meaningful answers and consisting solely of phrases including "*none*," "*no*," "*thank you*" or left blank were classified as "*Invalid*" and excluded from the analysis.

c. Coding Process and Negotiated Agreement

The coding process involved two researchers: the author of the current study and an independent secondary coder. First, both coders independently coded datasets based on a pre-developed technofeminist coding manual. The utilization of the codebook ensured alignment with a unified theoretical framework, consequently enhancing intercoder neutrality and reliability (Braun & Clarke, 2006; Saldaña, 2021). The "*negotiated agreement*" strategy was employed to establish the reliability of coding. Garrison *et al.* (2006) stated that implementing a negotiation-based coding approach particularly increases intercoder reliability and strengthens the validity of the coding procedure. After independent coding sessions ended, two coders negotiated the discrepancies. During this process, the codebook and Wajcman's theoretical framework were considered as reference points. Initial disagreements were mainly due to overlooking the codes; almost complete consensus was achieved regarding which code was appropriate. At the end of this session, all the discrepancies were resolved through negotiation, yielding complete agreement. The negotiated agreement method establishes coding reliability without the necessity of calculating a statistical coefficient, as the shared understanding of the codebook sharpens (Garrison *et al.*, 2006; Campbell *et al.*, 2013).

3.4.3 Intersectionality Analyses

R and the Welch ADF packages were used for intersectionality analyses. In order to examine the common effects of social categories, two-way Welch–James factorial ANOVA was applied for four factor pairs (Gender × Grade Level, Gender × AI Training Status, Gender × AI Usage Frequency, Grade Level × AI Training Status). This method can test interaction effects in cases of unequal cell sizes and variance heterogeneity (Lix & Keselman, 1998). For each factor pair × outcome variable, all pairs of intersection cells were compared with Bonferroni correction; in addition, 16 omnibus interaction tests were considered as a separate multiple test family, and Bonferroni correction was applied. In addition, when calculating the general perception score, negative items (L12–L15) were reverse-coded. The ethics subscale was retained in its original direction; higher scores indicate greater ethical concern.

4. Results and Discussion

4.1 Findings

Consistent with the nature of a convergent parallel mixed-methods design, quantitative and qualitative findings are presented independently. While quantitative findings are constituted by statistical investigations based on scale measurements, qualitative findings emerge from thematic analysis of metaphorical content and open-ended responses. The integration of the two datasets has been presented under a separate heading.

4.1.1 Quantitative Findings

4.1.1.1 Demographic Findings

The demographic characteristics of the participants are presented in Table 1.

Table 1: Demographic Characteristics of Participants

Variable	Category	f	%
Age Group	17–20 years	64	42.7
	21–24 years	84	56.0
	25 years and over	2	1.3
Gender	Female	124	82.7
	Male	26	17.3
Grade Level	First year	37	24.7
	Second year	45	30.0
	Third year	33	22.0
	Fourth year	35	23.3
AI Training	Yes	51	34.0
	No	99	66.0
AI Usage Frequency	Rarely	21	14.0
	Several times a day	84	56.0
	Every day	45	30.0
Total		150	100.0

Note: Age was recoded into three groups (17–20, 21–24, 25+) to avoid low cell counts and to improve interpretability.

Among the 150 preservice preschool teachers in this study, 82.7% (n=124) were female, and 17.3% (n=26) were male. In terms of age, 42.7% (n=64) were in the 17–20 age range, 56.0% (n=84) were in the 21–24 age range, and 1.3% (n=2) were 25 years and older. Most of the sample (98.7%) was between the ages of 17–24. By academic year, 24.7% (n=37) of the participants were first-year students, 30.0% (n=45) were second-year, 22.0% (n=33) were third-year, and 23.3% (n=35) were fourth-year. While 34.0% (n=51) of the preservice preschool teachers had prior AI training, 66.0% (n=99) reported none. Regarding AI usage frequency, 14.0% (n=21) rarely used it, 56.0% (n=84) used it several times a day, and 30.0% (n=45) used it every day. In total, 86.0% of participants reported using AI at least several times a day.

4.1.1.2 Scale Descriptive Statistics and Reliability

Participants' perceptions of AI use in educational contexts were assessed using a five-point Likert-type scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument comprised three subscales: "Teaching Perception" (7 items), "Learning Perception" (4 items), and "Ethical Perception" (4 items). Reliability analyses yielded an overall Cronbach's alpha of 0.81 for the scale, indicating good internal consistency. Subscale alphas were 0.88 for Teaching Perception, 0.77 for Learning Perception, and 0.69 for Ethical Perception. Teaching and Learning Perception exceeded the conventional 0.70 criterion, whereas the Ethical Perception subscale fell slightly below this threshold but was retained given its acceptable reliability for exploratory research (DeVellis, 2016; Hair *et al.*, 2014). Descriptive statistics for the scale are presented in Table 2.

Table 2: Perceptions of AI in Education

Dimension	Item	N	Min	Max	M	SD	Skewness	Kurtosis	α
Teaching Perception	M1	150	3	5	4.21	0.57	-0.033	-0.299	0.88
	M3	150	1	5	4.09	0.68	-0.621	1.704	
	M5	150	1	5	4.22	0.73	-1.099	2.48	
	M8	150	2	5	4.05	0.78	-0.518	-0.134	
	M11	150	2	5	4.27	0.68	-0.521	-0.235	
	M13	150	2	5	3.98	0.78	-0.393	-0.274	
	M15	150	3	5	4.25	0.66	-0.32	-0.735	
Learning Perception	M4	150	1	5	3.52	1.09	-0.292	-0.651	0.77
	M6	150	1	5	3.89	0.91	-0.5	-0.237	
	M7	150	1	5	3.78	1.05	-0.752	-0.081	
	M10	150	1	5	3.73	1.04	-0.604	-0.227	
Ethical Perception	M2	150	1	5	1.28	0.84	2.954	7.690	0.69
	M9	150	1	5	2.03	1.19	0.59	-0.848	
	M12	150	1	5	1.32	0.85	2.502	5.094	
	M14	150	1	5	2.53	1.40	0.206	-1.245	
General		150							0.81

For Teaching Perception, mean scores ranged from 3.98 to 4.27. The lowest mean was observed for M13 (3.98), while the highest means were observed for M11 (4.27) and M15 (4.25). These values indicated high levels of agreement, with participants responding "Agree" or "Strongly Agree" to statements regarding AI's contribution to teaching. Standard deviations ranged from 0.57 to 0.78, suggesting that scores were relatively clustered around the mean. All items showed negative skewness, with particularly pronounced values for M5 (-1.099) and M3 (-0.62); positive and substantial kurtosis values appeared for M5 (2.48) and M3 (1.704). This pattern shows that the responses to these items are clustered toward high scores and exhibit a peaked distribution.

Item means within the learning perception dimension span from 3.52 to 3.89. While M4 yielded the lowest mean (3.52), M6 demonstrated the highest (3.89). These means indicated moderate agreement between "Undecided" and "Agree" regarding AI's impact on learning processes; and this level of agreement was lower than that observed for

Teaching Perception. Standard deviations ranged from 0.91 to 1.09, revealing that response variability was greater than the Teaching Perception dimension. Although negative, all skewness coefficients stayed below 1 in absolute value, with M7 recording the lowest (-0.752). Similarly, kurtosis values ranged from -0.651 to -0.081, suggesting a distribution that approximates normality.

The ethical perception subscale revealed that the mean score ranged from 1.28 to 2.53. M2 (1.28) had the lowest mean, while the highest mean was observed in M14 (2.53). These findings indicated that the participants reported low agreement, with their responses concentrated on “Strongly Disagree” and “Disagree”. The standard deviation of M14 (1.40) indicated greater response heterogeneity than other items in this subscale. The skewness values of M2 (2.954) and M12 (2.502) were positive and indicated apparent curvature. The kurtosis values for these same items were 7.69 and 5.094, respectively.

Overall, participants expressed positive viewpoints on AI’s instructional teaching aspect within the educational setting, whereas the learning dimension remained at moderate levels. Regarding ethical perception, participants reported low levels of ethical concern, as indicated by their disagreement with the ethical concern items.

4.1.1.3 Normality Test

The Kolmogorov-Smirnov test was conducted to determine the normality of the data distribution. Results are presented in Table 3.

Table 3: Normality Test Results for AI Use in Education

Variable	Statistics	df	p
Using AI in Education	.084	150	.011
Teaching Perception	.191	150	.000
Learning Perception	.127	150	.000
Ethical Perception	.203	150	.000

Note: N = 150. Statistics = Kolmogorov-Smirnov *D* statistic. A significant result ($p < .05$) indicates a deviation from normality.

According to the results of the test, all dependent variables were significant at the $p < .05$ level. As the dataset did not meet the normality assumption, non-parametric testing approaches, including the Mann-Whitney *U* test and the Kruskal-Wallis test, were employed to facilitate group comparisons across variables.

4.1.2 Comparative Analysis

4.1.2.1 Comparison of Gender and Artificial Intelligence Training Status

The Mann-Whitney *U* test was administered to determine whether statistically significant variations existed in perception scores concerning AI utilization in education based on participant gender and training status. Table 4 presents the results.

Table 4: Mann-Whitney U Test Results by Gender and AI Training Status

Variable	Group	N	Mean Rank	Sum of Ranks	<i>U</i>	<i>p</i>
Gender						
Using AI in Education	Female	124	76.03	9398.5	1575.5	.856
	Male	26	72.96	1926.5		
Teaching Perception	Female	124	75.80	9425.5	1548.5	.750
	Male	26	74.08	1899.5		
Learning Perception	Female	124	75.80	9399	1575.0	.853
	Male	26	74.08	1926		
Ethical Perception	Female	124	76.23	9235	1485.0	.518
	Male	26	72.02	2090		
AI Training Status						
Using AI in Education	Yes	51	83.16	4241	2134.0	.121
	No	99	71.56	7084		
Teaching Perception	Yes	51	82.74	4219.5	2155.5	.139
	No	99	71.77	7105.5		
Learning Perception	Yes	51	81.36	4149.5	2225.5	.231
	No	99	72.48	7175.5		
Ethical Perception	Yes	51	71.40	3641.5	2315.5	.395
	No	99	77.61	7683.5		

Note: $p < .05$

No statistically significant differences were identified in AI perception scores by gender. For the overall perception score, no statistically significant difference was observed between female participants (mean rank = 76.03) and male participants (mean rank = 72.96) ($U = 1575.5$; $p = .856$). Similarly, no significant variations were identified in subscales: Teaching Perception ($U = 1548.5$; $p = .750$), Learning Perception ($U = 1575.0$; $p = .853$), and Ethical Perception ($U = 1485.0$; $p = .518$). These results demonstrated that AI perception did not vary by gender.

The analysis of difference in AI perception scores based on prior AI training yielded no statistically significant result. Regarding the overall perception score, no statistically significant difference was observed between participants who had received prior AI training (mean rank = 83.16) and those who had not (mean rank = 71.56) ($U = 2134.00$; $p = .121$). No significant differences were observed in subscales: Teaching Perception ($U = 2155.50$; $p = .139$), Learning Perception ($U = 2225.50$; $p = .231$), and Ethical Perception ($U = 2315.50$; $p = .395$).

4.1.2.2 Comparison by Grade Level

As the assumption of normality was not met, perception scores according to year of study were analyzed using the Kruskal-Wallis H test, and the results are presented in Table 5.

Table 5: AI Use and Subscale by Grade Level: Kruskal-Wallis Test

Variable	Year of Study	N	Mean Rank	H	df	p
Using AI in Education	First year	37	77.86	1.239	3	.744
	Second year	45	77.69			
	Third year	33	77.44			
	Fourth year	35	68.36			
Teaching Perception	First year	37	81.96	1.597	3	.660
	Second year	45	75.93			
	Third year	33	69.14			
	Fourth year	35	74.11			
Learning Perception	First year	37	77.47	1.103	3	.776
	Second year	45	71.70			
	Third year	33	81.11			
	Fourth year	35	73.01			
Ethical Perception	First year	37	75.03	6.197	3	.102
	Second year	45	86.36			
	Third year	33	74.88			
	Fourth year	35	62.63			

Note: $p < .05$

Statistical analysis revealed no significant differences in perception scores across the year of study for any dependent variable. The results were for Using AI in Education ($H = 1.239$, $df = 3$, $p = .744$), for Teaching Perception ($H = 1.597$, $df = 3$, $p = .660$), for Learning Perception ($H = 1.103$, $df = 3$, $p = .776$), and for Ethical Perception ($H = 6.197$, $df = 3$, $p = .102$). When mean ranks were evaluated, first-year students displayed the highest mean rank for overall AI use (77.86), whereas fourth-year students had the lowest (68.36). For Teaching Perception, first-year students demonstrated the highest mean rank (81.96), and third-year students had the lowest (69.14). For Learning Perception, third-year students had the highest mean rank (81.11) and second-year students had the lowest (71.70). For Ethical Perception, second-year students had the highest mean rank (86.36), and fourth-year students had the lowest (62.63). However, none of these observed differences demonstrated statistical significance.

While the H value for Ethical Perception was numerically higher than those for the other dimensions ($H = 6.197$, $df = 3$, $p = .102$), the corresponding p -value remained beyond the established significance threshold ($p < .05$). The mean rank difference separating second-year and fourth-year students with approximately 24 points was considerable; however, this difference did not reach statistical significance. These findings collectively suggested that year of study does not substantially influence participants' perceptions of AI implementation in education, across teaching, learning, and ethical dimensions.

4.1.2.3 Comparison by AI Usage Frequency

To determine whether there were differences in perception scores among participants according to their frequency of AI usage, a Kruskal-Wallis H test was conducted. The results are presented in Table 6.

Table 6: AI Use and Subscales by AI Usage Frequency: Kruskal-Wallis Test

Variable	Frequency of Use	N	Mean Rank	H	df	p	Difference
AI Usage Frequency	Rarely	21	72.17	8.58	2	.01	3 > 1
	Several times a day	84	67.92				3 > 2
	Every day	45	91.20				
Teaching Perception	Rarely	21	71.10	11.19	2	<.001	3 > 2
	Several times a day	84	67.05				
	Every day	45	93.33				
Learning Perception	Rarely	21	70.74	6.23	2	.04	—
	Several times a day	84	69.52				
	Every day	45	88.89				
Ethical Perception	Rarely	21	82.24	0.97	2	.61	—
	Several times a day	84	76.03				
	Every day	45	71.37				

Note: $p < .05$. Difference column indicates statistically significant pairwise comparisons (e.g., $3 > 1$ = Every day > Rarely).

Statistically significant differences in general perception scores were identified across groups based on how often participants used AI tools ($H = 8.58$, $df = 2$, $p = .01$). Participants reporting daily usage demonstrated substantially higher mean ranks (91.20) in comparison to those who used AI rarely (72.17) and several-times-a-day (67.92). Based on Tamhane's post-hoc test results, daily users scored significantly higher than less frequent users (mean difference = 0.280, $p = .046$) and several-times-a-day users (mean difference = 0.277, $p = .006$).

Similarly, statistically significant differences were observed among usage frequency groups in the Teaching Perception ($H = 11.19$, $df = 2$, $p = .001$). The every-day users (93.33) scored substantially higher than the rarely-use (71.10) and several- times-a-day (67.05) groups. A statistically significant difference emerged between several times daily and every day users (mean difference = -0.345, $p = .002$).

A statistically significant difference was also found in the Learning Perception dimension ($H = 6.23$, $df = 2$, $p = .04$). However, the Tamhane post-hoc test revealed no significant pairwise comparisons (all $p > .05$). The lowest p -value was observed between several-times-a-day and every-day users at .058, remaining above the significance level. This result shows that despite the Kruskal-Wallis test achieved overall statistical significance, post-hoc procedures did not reveal significant pairwise differences among groups. In summary, the every-day users' mean rank (88.89) was numerically higher than that of the other groups (70.74 and 69.52), yet this elevation could not be statistically validated.

Within the Ethical Perception subscale, no statistically significant difference was identified among usage frequency categories ($H = 0.97$, $df = 2$, $p = .61$). Mean rank examination revealed that the rarely use group (82.24) had numerically higher values compared to the several-times-a-day (76.03) and every-day (71.37) groups, although this difference did not reach statistical significance.

4.1.3 Relationship Insights

4.1.3.1 Correlation Analysis

The Spearman's rank-order correlation was employed to identify the relationships between the overall score of the use of AI in education, its subscales and the AI usage frequency. Results are presented in Table 7.

Table 7: Spearman Correlation Coefficients between Variables

Variable	1	2	3	4	5
1. Using AI in Education	1.000				
2. Teaching Perception	.841**	1.000			
3. Learning Perception	.777**	.615**	1.000		
4. Ethical Perception	.399**	.057	.030	1.000	
5. AI Usage Frequency	.197*	.228**	.177*	-.079	1.000

Note: ** $p < .05$. * $p < .01$.

The findings revealed a strong, positive, and significant correlation with Teaching Perception ($r = .841$, $p = .000$). A strong positive and statistically significant correlation was observed with Learning Perception ($r = .777$, $p = .000$). A moderate positive and statistically significant association was found with Ethics Perception ($r = .399$, $p = .000$).

When the relationships between subscales were examined, a moderate positive and significant relationship was found between Teaching Perception and Learning Perception ($r = 0.61$, $p = .000$). On the other hand, there was no statistically significant relationship between Ethical Perception and Teaching Perception ($r = .057$, $p = .486$) and between Ethical Perception and Learning Perception ($r = .030$, $p = .717$).

A weak positive and significant relationship was found between AI usage frequency and the overall perception score ($r = .197$, $p = .016$) was detected. Similarly, a weak positive and significant relationship was found between Teaching Perception and AI usage frequency ($r = .228$, $p = .005$) and between Learning Perception and AI usage frequency ($r = .177$, $p = .030$). There was no significant relationship between Ethical Perception and AI usage frequency ($r = -.079$, $p = .334$).

4.1.3.2 Chi-Square Analysis

The chi-square independence test was conducted to examine the relationships between gender and the status of receiving artificial intelligence training and the frequency of using artificial intelligence tools, as presented in Table 8.

Table 8: Chi-Square Results for Gender, AI Training, and Usage Frequency

Variable	Category	Female (n)	Male (n)	Total (n)	χ^2	df	p
AI Training Status	Yes	41	10	51	.279	1	.60
	No	83	16	99			
	Total	124	26	150			
AI Usage Frequency	Rarely	16	5	21	3.349	2	.187
	Several times a day	67	17	84			
	Every day	41	4	45			
	Total	124	26	150			

Note: $p < .05$.

There was no statistically significant relationship between gender and AI training status ($\chi^2 = .279$, $df = 1$, $p = .60$). While 33.1% ($n = 41$) of the female participants reported receiving AI training, 66.9% ($n = 83$) reported not receiving any. Among male participants, 38.5% ($n = 10$) reported receiving training, and 61.5% ($n = 16$) reported not receiving any.

There was also no statistically significant relationship between gender and AI usage frequency ($\chi^2 = 3.349$, $df = 2$, $p = .187$). The distribution of AI usage frequency among female participants was as follows: 12.9% ($n = 16$) rarely, 54.0% ($n = 67$) several times a day, and 33.1% ($n = 41$) every day. The distribution among male participants was: 19.2% ($n = 5$) rarely, 65.4% ($n = 17$) several times a day, and 15.4% ($n = 4$) every day.

4.2 Qualitative Findings

4.2.1 Metaphorical Analysis

Of the 150 responses, 146 metaphors were included in the analysis. Four responses of “no perspective” were rejected as invalid data. The remaining metaphors were coded based on the technofeminist codebook and systematically categorized into seven main themes in Table 9.

Table 9: Distribution of Metaphor Themes and Subcodes

Subcode	Theme	f	%
Situated Knowledge vs. The God Trick	Algorithmic Bias and Data Politics	66	44.00
Deskilling	Labor and Material Conditions	29	19.33
The Illusion of Time Savings	Gendered Politics of Time	14	9.33
Domestication	Space and Digital Space	11	7.33
Assistant Metaphor	Relational Labor and Identity in Education	9	6.00
Education vs. Instruction	Relational Labor and Identity in Education	8	5.33
Sociotechnical Networks	Mutual Shaping	4	2.67
Bias Clearance	Algorithmic Bias and Data Politics	3	2.00
Infrastructural Gendering	Mutual Shaping	2	1.33
Total (valid metaphors)		146	100.00
Invalid responses	—	*4*	—
Total responses		150	—

Within the subcode Situated Knowledge vs. The God Trick ($f = 66$; %44.0), participants conceptualized AI as encyclopedias, libraries, professors, brains, sages, and crystal balls.

One participant described AI as *"a brain that holds more than one piece of information"* (ID 4), while another used the analogy of *"an omniscient professor"* (ID 19). Another participant noted *"it's like a crystal ball... you can learn by looking at whatever you want to learn"* (ID 62).

The Deskilling subcode (f = 29; %19.3) revealed that participants associated AI with images such as ready-made information, fast food, pacifiers, chocolate, black holes, sponges, and piggy banks with a hole in the bottom. While one participant considered it *"ready-made information"* (ID 2), another used the phrase *"it is like a black hole... once you get used to using it, it is the method of looking for a solution in every situation"* (ID 31). Another participant assumed, *"It is like fast food; once you get used to it, you don't buy ingredients and cook again"* (ID 119).

For the subcode Illusion of Time Saving (f = 14; %9.3), the participants depicted AI as the speed of light, cheetahs, airplanes, and cars, emphasizing AI's promise of speed. One participant considered, *"It is like the speed of light because it gives a lot of information almost instantly"* (ID 23), while another thought, *"It is like an airplane because it delivers the fastest information in the shortest time"* (ID 37).

In Domestication (f = 11; 7.3%), noteworthy constructs were food processors, navigation, play dough, cocoons, saplings, and roads, showing that AI is established as a tool shaped according to the pedagogical intention of the teacher. One participant mentioned, *"I liken artificial intelligence to a food processor... I determine the main ingredients and the essence of the recipe, and it saves me time to bring these ingredients to the desired consistency"* (ID 145). Another participant stated that *"it is like play dough because it behaves the way I shape it"* (ID 129). This theme appeared exclusively among female participants (female: 8.9%; male: 0.0%)

Participants who conceptualized AI as an assistive tool under the teacher's control were coded under Assistant Metaphor (f = 9; 6.0%). While one participant noted *"AI is like a human hand because it helps to make better use of time"* (ID 10), another said, *"It's like a helper because it helps me when I fall short"* (ID 76).

Robot metaphors were coded under Education vs. Instruction (f = 8; 5.3%). One participant responded, *"It is like a robot because it does not respond emotionally"* (ID 41), while another said, *"It is like a robot because it makes human life easier"* (ID 8).

The subcodes of Sociotechnical Networks (f = 4; 2.7%), Bias Clearance (f = 3; 2.0%) and Infrastructural Gendering (f = 2; 1.3%) were less represented at the metaphor level. Masculine Citadel, Programmer Culture, Unseen Digital Labor, Automation of Care Labor, Digital Panopticon, Gender Scripts, and Feedback Loops did not appear at the metaphor level despite being in the codebook.

4.2.2 Open-Ended Question Analysis

The responses to the three open-ended questions were coded consistently with the technofeminist codebook. Results are presented in Table 10.

Table 10: Distribution of Main Themes in Open-Ended Responses

Theme	Q1: Areas of AI Usage	Q2: Interaction with AI	Q3: General Thoughts about AI
Space and Digital Space	79 (52.7%)	10 (6.7%)	—
Mutual Shaping	10 (6.7%)	73 (48.7%)	42 (28.0%)
Relational Labor and Identity in Education	40 (26.7%)	63 (42.0%)	24 (16.0%)
Algorithmic Bias and Data Politics	17 (11.3%)	—	5 (3.3%)
Gendered Politics of Time	4 (2.7%)	3 (2.0%)	8 (5.3%)
Labor and Material Conditions	—	—	11 (7.3%)
Masculine Culture and Expertise	—	—	3 (2.0%)
Invalid	—	1 (0.7%)	57 (38.0%)
Total	150 (100%)	150 (100%)	150 (100%)

Note: Q1 = Areas of AI usage; Q2 = Interaction with AI; Q3 = General thoughts about AI. Dashes indicate that the theme did not appear for that question.

Regarding the ways participants integrate AI into their lives, five main themes emerged. The Space and Digital Space theme ($f = 79$; 52.7%) reflects participants' AI usage across personal, academic, social, and professional domains. A participant's statement, *"I use it whenever I need it; in my daily life... or whenever I feel the need for information in my class..."* (ID 27) illustrates this hybrid usage pattern. Within the Relational Labor and Identity in Education theme ($f = 40$; 26.7%), participants considered AI as an auxiliary tool in academic tasks such as homework, lectures, and exam preparation. One participant said, *"I use it when studying for exams, preparing projects, or preparing activities"* (ID 15). In the Algorithmic Bias and Data Politics theme ($f = 17$; 11.3%), participants utilized AI as a source of information. While one participant disclosed using it *"For the purpose of obtaining information"* (ID 5), another declared, *"Academic and information retrieval, organizing"* (ID 11). Within the Mutual Shaping theme ($f = 10$; 6.7%), participants positioned AI as a part of their lives. One participant said, *"Personal"* (ID 18), while another used the phrase *"Academy"* (ID 30).

In the theme of Gendered Politics of Time ($f = 4$; 2.7%), participants used AI to access information instantly. One participant admitted, *"I use it academically, that is, to quickly get information about things I don't know"* (ID 16).

When participants were asked about their interaction with AI, five main themes were identified (Table 10). With the theme of Mutual Shaping ($f = 73$; 48.7%), participants described a step-by-step negotiation interaction with AI. One participant explained, *"First, I clarify my purpose... I examine the answer and redirect it if there are any missing or disliked areas"* (ID 35), while another expressed, *"I ask the questions I am curious about; if the answer satisfies, I skip that question and ask other questions; if not, I ask the same question in more detail"* (ID 14).

In the theme of Relational Labor and Identity in Education ($f = 63$; 42.0%), participants interact with AI in a question-and-answer pattern. One participant said, *"Usually by asking questions"* (ID 3), while another used the phrase *"In the form of questions and answers"* (ID 5). Another participant said, *"I make sure to ask my questions in polite and*

formal language; I usually use an AI tool and consult with it" (ID 129). In the Space and Digital Space theme (f = 10; 6.7%), participants tended to confirm, check, and correct the AI output. One participant asserted, *"I ask the AI about the question or topic I want to get information about, and then I confirm the information"* (ID 10), while another declared, *"I check whether it is safe two or three times in my work"* (ID 21). In the theme of Gendered Politics of Time (f = 3; 2.0%), participants described the process with the logic of speeding up. One participant professed, *"I write what I want; I am careful not to drag it out too long. I quickly get the answer and close it"* (ID 52), while another said, *"AI responds quickly, but it is not always reliable"* (ID 121).

Despite the high rate of invalid responses in the general thoughts about AI question (f= 57; 38.0%), valid responses are concentrated in six main themes (Table 10).

In the Mutual Shaping theme with the highest frequency (f= 42; 28.0%), the inevitability of AI's role in education was emphasized. Participants stated that technology *"will affect whether we want it or not"* (ID 18) and that *"it needs to be studied more individually and subtly"* (ID 24).

In the Relational Labor and Identity in Education theme (f = 24; 16.0%), participants positioned AI as an assistive tool. One participant disclosed, *"It makes education easier"* (ID 3), while another assumed, *"AI is an assistive tool in education. It is useful if it can be used correctly"* (ID 20).

In the Labor and Material Conditions theme (f = 11; 7.3%), participants expressed concern about AI damaging intellectual labor. One participant noted, *"I think these tools accustom people to convenience, and therefore knowledge and science become worthless"* (ID 14), while another underlined, *"Students now ask AI about all their homework without thinking and analyzing it themselves"* (ID 101).

In the theme of Gendered Politics of Time (f = 8; 5.3%), participants expressed their expectations for the accelerated spread of AI. One participant articulated, *"I think AI will be a tool that people will use and need more in the future"* (ID 29), while another voiced, *"The future will be shaped by this"* (ID 74).

In the Algorithmic Bias and Data Politics theme (f = 5; 3.3%), participants addressed the problem of accuracy and reliability of AI. One participant thought, *"AI is easy, yes, but we should not depend only on its answer when learning some information because it can also make mistakes"* (ID 127), while another said, *"Everything it says has a dangerous dimension for people who think it is absolutely true"* (ID 87). This theme appeared exclusively among female participants (female: 4.0%; male: 0.0%).

In the Masculine Culture and Expertise theme (f = 3; 2.0%), participants stated that AI education should begin at an early age. One participant suggested, *"AI education should start at a young age"* (ID 10), while another assumed, *"It seems to be at the forefront of education; even teachers will need to renew themselves"* (ID 5). This theme also appeared exclusively among female participants (female: 2.4%; male: 0.0%).

4.2.3 Intersectional Findings

Two-way Welch–James factorial ANOVA was conducted to examine intersectional effects. Among the 16 omnibus interaction tests, only the Grade Level $\times$ AI Training Status $\rightarrow$ Teaching Perception interaction was statistically significant at $*p < .05$ ($F = 3.608$, $p = .048$, partial $\eta^2 = .054$). However, this effect lost significance when the Bonferroni correction was applied for the 16 tests (adjusted $p = .766$). Post-hoc comparisons showed that first-year students who had received AI training ($M = 4.36$, $n = 25$) reported higher teaching perception than those who had not ($M = 3.77$, $n = 12$; Bonferroni-adjusted $p = .022$). However, this finding is exploratory and was not replicated at other grade levels. All other interaction effects (Gender $\times$ Grade Level, Gender $\times$ AI Training Status, Gender $\times$ AI Usage Frequency) were not statistically significant (all $p > .05$). Overall, no significant intersectional effects were found between demographic variables.

4.4 Discussion

The purpose of this study was to investigate perception levels and metaphors used by preservice preschool teachers regarding AI. A critical analytical framework was adopted to move beyond technological determinism and “digital equity” discourses. Quantitative scale trends, qualitative metaphor categories, and the intersectionality of both datasets were synthesized within a technofeminist framework (Wajcman, 1991, 2004, 2010). This study offers a nuanced understanding of the intersection of gender, occupational identities, care ethics, and sociotechnical structures.

While the initial research question investigated the level of perception, the first sub-question examined differences by demographics. The most critical observation derived from the quantitative data was that perception was not a unidimensional “attitude”; rather, it was structured as a multilayered evaluation system whose components operated independently of one another. Preservice preschool teachers’ perception of AI in teaching was distinctly positive, yet their perception of learning was more cautious. While there was a strong positive association between teaching and learning perceptions, ethical perception was not statistically significantly related to either dimension.

Wajcman’s technofeminist framework explains the disconnect among these variables. Wajcman (2004) argues that technology is never a neutral tool; rather its design, use, and meaning are shaped within a sociotechnical network. This network is embedded in relations between power and gender. This dissociation between ethics and pedagogy stemmed from participants viewing AI primarily as a tool for efficiency and benefit, while failing to connect it to dimensions of responsibility and power within the same framework.

This finding partially aligns with the existing literature. Özaydın Aydoğdu and Aydoğdu (2025) and Kaya and Köseoğlu (2024) reported that pedagogical approval and risk perception function independently. However, Gençaslan *et al.* (2024) found a moderate positive relationship between pedagogical evaluation and general attitude among in-service teachers. This divergence can be explained by the sample difference.

Participants without classroom management experience viewed AI as an abstract technical facilitator, while in-service teachers integrated ethical responsibility and pedagogical benefit as natural components of professional practice.

This disconnect reflects the use/abuse model that Wajcman (1991) criticizes, because treating technology as a neutral tool obscures the gendered values and ethical implications it carries. Wajcman's argument that "*technology is a culture that expresses and reinforces relationships between men*" (p. 22) makes this dynamic even clearer. The professional identity of preschool teaching, defined by care labor, makes it difficult to incorporate AI as a purely technical skill. This can be read as an argument that women are expected to renounce their gender identity when entering the technical field (Wajcman, 1991).

Gender, grade level, and AI training status did not have a significant effect on overall perception. These non-significant results align with the findings reported by Özaydın Aydoğdu and Aydoğdu (2025) and Gençaslan *et al.* (2024). However, these non-significant results are not universal. Gölbaşı and Okul (2024) found that male students demonstrated higher technology use than female students.

While AI usage frequency strengthened teaching perception, it did not influence ethical perception. This dissociation reflects Wajcman's (2004) concepts of interpretive flexibility and domestication. Frequent use accelerates domestication, yet it does not question the values technology carries (pp. 37, 46–48). Domestication makes technology manageable, not transformative.

In the intersectional analysis, only the interaction between grade level and AI training status was initially significant before Bonferroni correction, and this effect disappeared after correction. This finding aligns with Wajcman's (2004) argument that the relationship between gender and technology is historically and socially constructed. Perceptions of AI are shaped by multiple factors, not a single variable. The disappearance of this interaction may reflect the limited sensitivity of the scale rather than the absence of a meaningful effect (Wajcman, 1991).

Preservice preschool teachers' association of AI with cognitive resources, including books, encyclopedias, and sagacity, aligns with the empirical findings (Balıkçı *et al.*, 2024; Demir Evcimen *et al.*, 2025; Sayın & Orbay, 2025; Şentürk & Akol Göktaş, 2024). In contrast, the symbolic characterization of AI through dependency-related objects such as cigarettes, pacifiers, and chocolate differs from the studies by Güneyli *et al.* (2026), Lim (2024), Hu *et al.* (2025), and Korkmaz and Çilsalar Sağnak (2024). This discrepancy can be explained by differences in sample characteristics, cultural frameworks, and methodological approaches.

Wajcman's (1991) critique of the use/abuse model helps explain this pattern, as viewing technology as a neutral instrument obscures how its design carries gendered power relations. The participants' characterization of AI as both a "*wise professor*" and a "*pacifier and cigarette*" demonstrated how they attribute deskilling effects to individual misuse, thereby rendering AI's intrinsic power relations invisible.

In other studies, the clustering of metaphors around technofeminist dimensions confirmed that AI was not a neutral tool, but a sociotechnical system interwoven with gender and labor (Küçükkara *et al.*, 2024; Kalaba Yıldırım & Önder, 2025). Traditional metaphor studies (Ağmaz & Ergüleç, 2024; Savaşkan, 2024; Şentürk & Akol Göktaş, 2024), however, categorized metaphors within gender-neutral frameworks. This discrepancy in outcomes can be attributed to the distinct methodologies employed in the data analysis. Descriptive analysis focuses on surface-level similarities, while technofeminist analysis underscores the significance of care work, time pressure, and the erosion of technical skills.

These key concepts elaborate the pattern further. The God trick positions AI as a neutral supreme authority, though this is an illusion (Wajcman, 2004). Deskilling refers to the relinquishment of the teacher's mental autonomy, reflecting the broader pattern in which technology is "*designed by men, for men*" (Wajcman, 1991, pp. 27, 158-159). Relational labor signifies the sacrifice of teaching's emotional dimension to technological objectivity, a dynamic consistent with Wajcman's (1991) critique of technology's gendered rationality. Gendered Politics of Time reflects pressures of speed and efficiency (Wajcman, 2004). Domestication is the process of taming foreign technology, embedded in designers' gendered assumptions (Wajcman, 2004). Sociotechnical networks show AI to be a "*seamless web*" (Wajcman, 2004, p. 106). Infrastructural gendering emphasizes that sexism remains "*hidden in the deepest layers of code*" (Wajcman, 1991, p. 22).

Female participants' relational metaphors ("*mirror, confidant, mother*") and male participants' instrumental metaphors ("*robot, machine*") found support in the literature (Aktaş, 2026; Kandır & Temel, 2025; Demir Evcimen *et al.*, 2025; Balıkçı *et al.*, 2024). Although studies by Hu *et al.* (2025), Savaşkan (2024), and Korkmaz and Çilsalar Sağnak (2024) reported no significant differences between genders, their samples were drawn from different disciplines and professional contexts. Since professional identity in preschool teaching is built on care and relational practice (Noddings, 2013), participants humanize AI; consequently, studies with different samples may reach different findings. This pattern can be explained by two of Wajcman's (1991, 2004) concepts, namely the gendered culture of technology and women's exclusion from technical domains. Technology is "a culture that expresses and reinforces relationships between men" (Wajcman, 1991, p. 22), and male participants' mechanical images stem from this cultural framing. Women, in turn, are expected to renounce their gender identities to enter technical domains (Wajcman, 1991). Female participants' domestication of AI as "*mother and confidant*" mirrors their exclusion from technical fields and confinement to care. Yet this strategy narrows technology to a specific domain rather than transforming its gendered structure (Wajcman, 2004).

The last research question asked how quantitative perception levels and qualitative metaphor themes converge, diverge, or complement each other in a technofeminist reading of AI. Frequent use strengthened Teaching Perception and aligned with metaphors like "*always with me.*" This fit Wajcman's (2004) concept of interpretive flexibility, in which a practical relationship makes the tool one's own (p. 37).

Yet this convergence created an illusion of neutrality. As use increased, critical scrutiny of AI's neutrality may diminish, consistent with Wajcman's (1991) critique of the use/abuse model. By contrast, quantitative measures showed ethical concern as unrelated to Teaching and Learning Perceptions. This contrasted with qualitative data, in which metaphors such as *"ready-made information," "cigarette,"* and *"pacifier"* were strongly expressed. If ethical concern was not integrated into the same evaluative plane as Teaching Perception, participants framed it as an *"individual use problem."* Technology's inherent power relations remain invisible (Wajcman, 1991, p. 63). Qualitative data brought this discursive layer into view, which the quantitative scale could not capture.

Quantitative analyses showed no Grade Level differences in perception. Yet qualitative data revealed fourth-year participants voicing anxieties about unemployment and being replaced by AI. This indicated an emotional layer that the scale format failed to capture. Together, the three patterns showed the explanatory role of domestication. Participants adapted AI to their own practices, but this adaptation did not involve questioning the values it carries. Quantitative measurement reported ethical dissociation as an absence, while qualitative metaphors exposed its symbolic mechanisms. By evaluating both datasets together, the technofeminist reading made visible how the acceptance of AI in teaching was separated from professional identity and ethical responsibility (Wajcman, 2004).

These findings supported two of Wajcman's (1991, 2004) arguments. First, technology is not a neutral instrument but an arena that reproduces social relations. When users evaluate it within the use/abuse model, its gendered values are rendered invisible. Second, women entering technical domains are often expected to relinquish relational and ethical aspects of professional identity (Wajcman, 1991). As Wajcman (2004) observes, *"the direction of technological change depends on the forms of agency that shape it"* (p. 114). Unless ethical pedagogical thinking becomes a key part of AI integration, using AI may remain an additional concern for teachers.

4.5 Limitations

This study has four limitations. First, qualitative data were drawn from written metaphor responses instead of interviews, which limited the depth of interpretive insight. Second, the concurrent design confined integration to an interpretive level and prevented causal inference. Third, the sample's predominantly female and young demographic composition restricted generalizability. Fourth, the high rate of invalid responses to the general opinion question limited the qualitative depth of this dimension. Despite these limitations, the study makes an original contribution to the literature as one of the first mixed-methods studies of preservice preschool teachers' AI perceptions from a technofeminist perspective.

5. Recommendations

For teacher education, AI-related coursework should move beyond technical skills and incorporate epistemic dimensions such as algorithmic bias, data politics, and situated knowledge. AI should also be framed in ways that reinforce preservice preschool teachers' professional identity. AI can serve as a reflective tool for teachers to interrogate their own practices.

For policymakers, gender should be central to AI integration in early childhood education. The relational metaphors used by female preservice teachers point toward materials that emphasize AI's potential to support care labor and relational pedagogy.

For researchers, future studies should adopt longitudinal mixed-methods designs to clarify causal relationships among perception layers. Experimental studies should test the long-term effects of AI training on ethical perceptions and professional identities, while interviews and focus groups should enrich qualitative data. Wajcman's framework should be tested across cultural contexts, and gender-centered policies and curricula should be prioritized.

6. Conclusion

This study explored how preservice preschool teachers perceived AI and conceptualized it through metaphors, using a technofeminist lens. The findings revealed a multilayered evaluation system with three dimensions: teaching perception, learning perception, and ethical perception. While teaching and learning perceptions were strongly associated with each other, ethical perception operated independently of both. Metaphors like "*the God trick*," "*deskilling*," and "*domestication*" revealed the symbolic mechanisms behind this separation.

The integration of quantitative and qualitative methods revealed points of convergence, divergence, and complementarity. Quantitative measures captured the dissociation between ethics and pedagogy as an absence of statistical relationship, while qualitative metaphors exposed its symbolic mechanisms. This suggests that acceptance of AI in education is separate from professional identity and ethical responsibility.

These results support Wajcman's (1991, 2004) arguments that technology is not neutral and that women entering technical domains are often expected to relinquish their personal values and beliefs. The study contributes to the literature by demonstrating that AI is not a neutral tool in early childhood education but is actively shaped by gendered structures.

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Conflict of Interest Statement

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The author has no relevant financial or non-financial interests to disclose.

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