

The Effect of Algorithm Explanation Detail on Consumer Response: A Serial Mediation Model via Perceived Fairness and Control

Zheyu Wang

*School of Management, Zhejiang University of Technology, Hangzhou, China
302023660041@zjut.edu.cn*

Abstract. As AI and big data reshape e-commerce, personalized recommendations are vital for boosting conversion and engagement. Yet most algorithms operate as "black boxes," fueling consumers' distrust and resistance, sparking urgent interest in transparent, explainable systems. While prior research treats explanations as simply "present" or "absent," it overlooks how explanation detail, underlying cognitive pathways (e.g., fairness and control perceptions), and dual outcomes (purchase intention and brand attitude) interact. Grounded in procedural justice and self-determination theories, this study proposes a serial dual-mediation model: explanation detail → perceived algorithmic fairness → perceived control → consumer response. A between-subjects experiment with 240 experienced online shoppers tested three conditions: no explanation, simple explanation, and detailed explanation. Using PROCESS Model 6 (5,000 bootstraps), results reveal a critical information-density threshold: only detailed explanations significantly enhance perceived algorithmic fairness; simple explanations do not differ significantly from no explanation. Perceived algorithmic fairness plays a key mediating role between explanation detail and both purchase intention and brand attitude, indicating that detailed explanations exert their influence primarily through fairness perception rather than directly. Moreover, the serial path (detail → fairness → control → response) is significant, suggesting that perceived control emerges only after fairness is established. These findings clarify when and how explanations work, uncover the cognitive mechanism linking transparency to consumer response, and offer actionable guidance for designing effective, trustworthy recommendation systems.

Keywords: Algorithm explanation, perceived algorithmic fairness, perceived control, purchase intention, brand attitude

1. Introduction

With the deepening application of artificial intelligence and big data, personalized recommender systems are now widely embedded in e-commerce operations and are used to improve platform conversion efficiency and user retention [1]. However, mainstream recommendation algorithms largely operate as "black boxes," leaving consumers unable to understand the underlying recommendation logic and resulting in eroded trust and behavioral resistance [2]. The introduction

of regulations, including China's Personal Information Protection Law and the EU's GDPR has further boosted users' demand for algorithmic transparency, and the design of recommendation explanations has become a shared concern of industry and academia.

Three gaps remain in the existing literature. First, prior studies have typically treated "whether an explanation is provided" as a binary variable and have overlooked gradations in explanation detail. Second, most work has focused on the direct effect of explanations and has paid limited attention to the cognitive mediating pathways through which they shape consumer behavior. Third, the existing literature has mostly focused on the effect of algorithm explanations on single attitudinal outcomes such as system trust, user satisfaction, or recommendation adoption intention, yet purchase intention (behavioral intention construct) and brand attitude (brand evaluation construct) are seldom jointly explored in one mediation model [2-4]. Drawing on procedural justice theory and self-determination theory, this study examines how explanation detail influences consumers' purchase intention and brand attitude through the serial cognitive pathway of "perceived algorithmic fairness → perceived control" and aims to reveal the psychological mechanism behind how algorithm explanations affect consumer responses.

2. Literature review and hypotheses

2.1. Algorithm explanation detail and perceived algorithmic fairness

Algorithm explanation detail refers to the breadth of information and logical completeness disclosed by a recommender system during the explanation process. Based on Chatti et al.'s classification of explanation granularity in recommendation systems, this study operationalizes explanation detail at three levels: no explanation (the recommendation result is shown without any accompanying statement), simple explanation (only the behavioral source of the recommendation is indicated, e.g., "based on your browsing history"), and detailed explanation (the underlying data sources, behavioral logic, and preferences of similar users are disclosed in full) [5].

Prior research on algorithmic fairness shows that users' perceptions of procedural transparency, consistency, and explainability substantially affect their fairness judgments [6]. Algorithm explanations that are informative and logically coherent help users understand the recommendation rules, reduce information asymmetry, and improve their evaluation of the algorithm [3]. Accordingly, this study proposes: H1: Algorithm explanation detail positively influences perceived algorithmic fairness.

2.2. Perceived algorithmic fairness and perceived control

Perceived control, grounded in self-determination theory, refers to an individual's ability to understand, anticipate, and exert agency over an event [7]. Prior studies have often treated algorithm explanations as a direct antecedent of perceived control. This pathway, however, presupposes that users actually trust and accept the disclosed information; if users remain skeptical of an explanation, mere information disclosure is unlikely to translate into a sense of control [4]. This suggests that the formation of perceived control is conditional on prior cognitive evaluation.

Procedural justice theory provides the key link: when an algorithmic procedure is perceived as transparent and rule-compliant, users first develop a clear understanding of the procedure, then form trust in the system's orderliness, and eventually convert this into a sense of agency over the recommendation context [8]. Shin similarly finds that fairness perceptions positively influence user

agency, supporting this causal sequence [2]. Accordingly: H2: Perceived algorithmic fairness positively influences perceived control.

2.3. Purchase intention, brand attitude, and the mediation mechanism

Purchase intention refers to a consumer's behavioral tendency and subjective likelihood of buying a product or service in a given context, while brand attitude refers to a consumer's overall evaluation of a brand [9, 10]. A positive fairness perception enhances consumers' trust in, and acceptance of, algorithmic recommendations, thereby fostering more favorable evaluations of both the recommended outcomes and the platform [11]. A heightened sense of control, in turn, leads users to regard the recommender system as a decision-aiding tool rather than a manipulative device, strengthening their purchase intention and brand affinity [12]. Accordingly: H3a/b: Perceived algorithmic fairness positively influences purchase intention / brand attitude. H4a/b: Perceived algorithmic fairness mediates the effect of explanation detail on purchase intention / brand attitude. H5a/b: Perceived control positively influences purchase intention / brand attitude. H6a/b: Perceived control independently mediates the effect of explanation detail on purchase intention / brand attitude. H7a/b: Perceived algorithmic fairness and perceived control serially mediate the effect of explanation detail on purchase intention / brand attitude.

2.4. Research model

This study takes algorithm explanation detail (none / simple / detailed) as the independent variable, perceived algorithmic fairness (M1) and perceived control (M2) as serial mediators, and purchase intention and brand attitude as outcome variables. Gender, age, online-shopping frequency, product involvement, and familiarity with recommender systems are included as control variables to enhance the robustness of the estimates. The hypothesis labels in Figure 1 (H1–H7) correspond one-to-one with the hypotheses stated above; H4, H6, and H7 represent the indirect-path combinations of $H1 \times H3$, $H5$, and $H1 \times H2 \times H5$, respectively, and are tested in Sections 4.5–4.6.

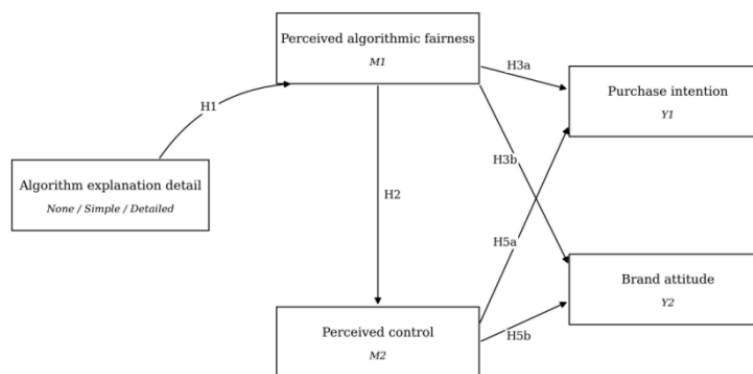


Figure 1. Theoretical model of serial mediation

3. Method

3.1. Research ddesign

This study adopts a single-factor three-level between-subjects scenario experiment design. The scenario was set in an e-commerce platform recommending Bluetooth headphones, using a fictitious brand to rule out pre-existing brand attitudes. The three groups of stimulus materials varied solely in

explanatory descriptions of recommendations: the no-explanation group viewed only a "You may like" prompt; the simple-explanation group viewed a single line stating "Recommended based on your browsing history"; while the detailed-explanation group obtained an elaborate statement illustrating browsing records, collected favorites, and peer user preferences behind the recommendation. Participants were randomly assigned to one condition, read the scenario, and completed the questionnaire. A manipulation-check item was used to verify that participants correctly identified the condition to which they had been assigned.

3.2. Sample and measures

The target population consisted of adult consumers with prior online shopping experience. Data were collected via an anonymous online questionnaire, with respondents randomly assigned to conditions. Responses showing patterned answers or unusually short completion times were treated as invalid and excluded. Measurement items of core variables were adapted from validated scales in existing literature and revised to fit the e-commerce recommendation scenario [2, 9, 13, 14]. All items were scored on a five-point Likert scale. To mitigate common method bias, the questionnaire was administered anonymously and used a paged layout; Harman's single-factor test was used as a preliminary diagnostic. Data analyses were conducted using SPSS and the PROCESS macro and proceeded sequentially through one-way ANOVA, reliability and validity testing, and a bootstrap serial mediation test with 5,000 resamples (Model 6).

4. Results

4.1. Sample description, reliability and validity

Table 1. Sample demographics (N = 240)

Variable	Category / Frequency	Variable	Category / Frequency
Gender	Male 104 (43.3%)	Monthly spending	< ¥500: 109 (45.4%)
	Female 132 (55.0%)		¥500–1,000: 75 (31.3%)
	Other 4 (1.7%)		¥1,001–3,000: 40 (16.7%); > ¥3,000: 16 (6.7%)
Age	18–24: 76 (31.7%)	Shopping frequency	Rarely: 10 (4.2%)
	25–34: 101 (42.1%)		1–2 times/week: 138 (57.5%)
	35–44: 48 (20.0%)		3–5 times/week: 69 (28.8%)
	≥ 45: 15 (6.3%)		Almost daily: 23 (9.6%)
Education	High school or below 25 (10.4%)		
	College 98 (40.8%);		
	Bachelor 91 (37.9%)		
	Master or above 26 (10.8%)		

Table 2. Descriptive statistics and reliability (N = 240)

Construct (items)	α	M (SD)
Perceived algorithmic fairness (5)	.862	3.257 (0.931)
Perceived control (5)	.855	3.279 (0.906)
Purchase intention (4)	.814	3.185 (0.922)
Brand attitude (5)	.842	3.277 (0.902)
Recommender familiarity (3)	.784	3.149 (0.962)
Product involvement (3)	.762	2.985 (0.908)

Note. CR and AVE values from CFA met conventional thresholds (CR > .70, AVE > .50).

A total of 240 valid responses were collected, with 80 participants in each condition. The demographic characteristics of the sample are presented in Table 1. The three experimental groups did not differ significantly on any demographic variable ($F_s < 1.7$, $p_s > .19$), indicating successful random assignment and good between-group comparability. All latent variables yielded Cronbach's $\alpha \geq .76$ (Table 2). CFA results showed CR > .70 and AVE > .50 across constructs, indicating satisfactory convergent and discriminant validity. Harman's single-factor test indicated that the first factor accounted for 34.48% of the variance (< 40%), suggesting that no severe common-method bias was evident at the preliminary diagnostic stage.

4.2. Manipulation check

A chi-square test was conducted to assess the effectiveness of the experimental manipulation. Participants' identification of the explanation condition closely matched their actual assignment, with the correct identification rate exceeding 95% in every group, $\chi^2(4) = 480.00$, $p < .001$. The manipulation check items corresponded closely to the experimental stimuli, indicating that the manipulation was successful.

4.3. One-way ANOVA: main effects

A one-way ANOVA was conducted with explanation detail (three levels) as the independent variable. The results for the focal variables are presented in Table 3.

Table 3. One-way ANOVA results (N = 240)

Dependent variable	Group 1	Group 2	Group 3	F	p	η^2
Perceived algorithmic fairness	2.97 (0.96)	3.27 (0.89)	3.53 (0.87)	7.571	.001	.060
Perceived control	3.23 (0.94)	3.31 (0.87)	3.30 (0.91)	0.199	.819	.002
Purchase intention	3.02 (0.83)	3.18 (0.90)	3.36 (1.00)	2.769	.065	.023
Brand attitude	3.09 (0.92)	3.27 (0.91)	3.47 (0.84)	3.676	.027	.030

Note. Group 1 = no-explanation; Group 2 = simple-explanation; Group 3 = detailed-explanation. η^2 values of .01 / .06 / .14 correspond to small / medium / large effects.

Between-group differences in perceived algorithmic fairness were significant, $F(2, 237) = 7.571$, $p = .001$, $\eta^2 = .060$. Bonferroni post-hoc tests showed that the detailed-explanation group ($M = 3.53$) scored significantly higher than the no-explanation group ($M = 2.97$; mean difference = 0.558, $p =$

.001), whereas the simple-explanation group ($M = 3.27$) did not differ significantly from either of the other groups ($ps > .10$); H1 was thus partially supported. The pattern suggests an information-density threshold: only sufficiently rich explanations produced detectable shifts in fairness perception. Perceived control did not differ significantly across the three conditions, $F = 0.199$, $p = .819$, $\eta^2 = .002$, indicating no direct main effect of explanation detail on control; within the serial mediation framework, this effect is expected to be transmitted through fairness, as examined in Section 4.5. Between-group differences in brand attitude were significant, $F = 3.676$, $p = .027$, with the detailed-explanation group ($M = 3.47$) significantly higher than the no-explanation group ($p = .020$). The between-group difference in purchase intention did not reach conventional significance, $F = 2.769$, $p = .065$, but the means showed a monotonically increasing pattern ($3.02 \rightarrow 3.18 \rightarrow 3.36$).

4.4. Correlation analysis

The correlation matrix for the focal variables is presented in Table 4.

Table 4. Correlation matrix

Variable	1	2	3	4	5	6
1. Perceived algorithmic fairness	1	.291***	.452***	.441***	.063	.212***
2. Perceived control		1	.403***	.383***	.199**	.170**
3. Purchase intention			1	.371***	.225***	.222***
4. Brand attitude				1	.215***	.219***
5. Recommender familiarity					1	.310***
6. Product involvement						1

Note. * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed); unmarked coefficients are not significant ($p > .05$).

Perceived algorithmic fairness showed moderate positive correlations with purchase intention ($r = .452$) and brand attitude ($r = .441$), and perceived control was also significantly correlated with purchase intention ($r = .403$) and brand attitude ($r = .383$, all $ps < .001$), providing preliminary support for H3 and H5. The correlation between the two mediators ($r = .291$, $p < .001$) was moderate, ruling out severe multicollinearity and meeting the precondition for serial mediation testing.

4.5. Serial mediation path analysis (H2–H7)

PROCESS Model 6 was used with the independent variable dummy-coded (reference group = no-explanation), controlling for gender, age, online-shopping frequency, familiarity with recommender systems, and product involvement.

The detailed explanation condition yielded significantly higher perceived algorithmic fairness ($B = 0.540$, $SE = 0.142$, $t = 3.815$, $p < .001$), indicating that greater explanation detail effectively strengthens consumers' perception of procedural fairness. Perceived algorithmic fairness in turn significantly and positively predicted perceived control ($B = 0.269$, $SE = 0.063$, $\beta = .276$, $p < .001$), supporting H2: when users view the recommendation process as fairer and more transparent, their perceived system control will rise correspondingly.

At the outcome level, perceived algorithmic fairness significantly predicted both purchase intention ($\beta = .350$, $p < .001$) and brand attitude ($\beta = .328$, $p < .001$), supporting H3a and H3b.

Perceived control likewise significantly predicted purchase intention ($\beta = .259$, $p < .001$) and brand attitude ($\beta = .253$, $p < .001$), supporting H5a and H5b.

After both mediators were entered, the direct effect of detailed explanation on purchase intention ($B = 0.102$, $p = .416$) and on brand attitude ($B = 0.172$, $p = .173$) no longer reached significance. Taken together with the significant indirect effects reported in Section 4.6, this pattern is best characterized as indirect-only transmission, meaning that the influence of explanation detail operates mainly via cognitive mediating paths.

4.6. Bootstrap tests of indirect effects (H4, H6, H7)

A bootstrap procedure with 5,000 resamples was used to test the indirect effects. The results are reported in Table 5. The indirect effects through perceived algorithmic fairness are significant. Specifically, the indirect effect of "detailed explanation $\rightarrow$ fairness $\rightarrow$ purchase intention" is 0.187, 95% BC-CI [0.079, 0.314], and that of "detailed explanation $\rightarrow$ fairness $\rightarrow$ brand attitude" is 0.171, 95% BC-CI [0.073, 0.293]. H4a and H4b are therefore supported.

The serial mediation paths are also significant. The indirect effect of "detailed explanation $\rightarrow$ fairness $\rightarrow$ control $\rightarrow$ purchase intention" is 0.038, 95% BC-CI [0.013, 0.076], and that for brand attitude is 0.037, 95% BC-CI [0.011, 0.077], indicating that detailed explanations affect consumer responses via the sequential fairness-control mediating mechanism. H7a and H7b are therefore supported.

Table 5. Bootstrap results for indirect effects (5,000 resamples)

Path	IE	Boot SE	95% BC-CI	Hypothesis
IE ₁ Detailed $\rightarrow$ Fairness $\rightarrow$ Purchase intention	0.187	0.059	[0.079, 0.314]	H4a ✓
IE ₂ Detailed $\rightarrow$ Fairness $\rightarrow$ Control $\rightarrow$ Purchase intention	0.038	0.016	[0.013, 0.076]	H7a ✓
IE ₃ Detailed $\rightarrow$ Control $\rightarrow$ Purchase intention	0.013	0.026	[-0.066, 0.098]	H6a ✗
IE ₁ Detailed $\rightarrow$ Fairness $\rightarrow$ Brand attitude	0.171	0.056	[0.073, 0.293]	H4b ✓
IE ₂ Detailed $\rightarrow$ Fairness $\rightarrow$ Control $\rightarrow$ Brand attitude	0.037	0.016	[0.011, 0.077]	H7b ✓
IE ₃ Detailed $\rightarrow$ Control $\rightarrow$ Brand attitude	0.012	0.025	[-0.063, 0.093]	H6b ✗

Note. ✓ indicates that the 95% bias-corrected CI excludes zero (significant indirect effect); ✗ indicates that the CI includes zero (non-significant).

By contrast, the independent mediating effect of perceived control is not significant, with both confidence intervals containing zero; H6a and H6b are therefore not supported. This reveals that algorithmic explanations fail to enhance perceived control in a direct manner but instead activate control indirectly through the prior formation of fairness perceptions.

4.7. Summary of hypothesis testing

Taken together, all hypotheses are supported or partially supported except H6a and H6b. Detailed algorithm explanations significantly enhance consumers' perceived algorithmic fairness and, through the serial "fairness-control" pathway, influence purchase intention and brand attitude. Perceived algorithmic fairness acts as a core mediator converting explanatory effects into user behavioral outcomes, whereas perceived control contributes primarily through the serial pathway rather than as an independent mediator.

Table 6. Summary of hypothesis testing

Hypothesis	Content	Key statistic	Result
H1	Explanation detail → fairness	$F = 7.571, p = .001$	Partially supported (detailed only)
H2	Fairness → control	$B = 0.269, p < .001$	Supported
H3a/b	Fairness → purchase intention / brand attitude	$\beta = .350 / .328, p < .001$	Supported
H4a/b	Fairness mediates explanation → outcome	$IE = .187 / .171, CI$ excludes 0	Supported
H5a/b	Control → purchase intention / brand attitude	$\beta = .259 / .253, p < .001$	Supported
H6a/b	Control independently mediates explanation → outcome	$IE = .013 / .012, CI$ includes 0	Not supported
H7a/b	Serial mediation: fairness + control	$IE = .038 / .037, CI$ excludes 0	Supported

Note. "Partially supported" for H1 indicates that only the detailed-explanation condition (vs. no-explanation) reached significance; the H4 and H7 effects are also observed only in the detailed-vs.-no-explanation contrast.

5. Discussion

5.1. Key findings

Only detailed explanations significantly enhanced perceived algorithmic fairness, while simple explanations did not differ significantly from no explanation. This indicates that algorithm explanations do not "work as long as they exist"; their effectiveness depends on a certain degree of informational richness. Single-source cues cannot effectively boost users' perceived procedural fairness, whereas detailed explanations that disclose the underlying logic and data improve perceptions of platform transparency and procedural soundness. This finding echoes ongoing debates in the explainable recommendation literature stressing explanation quality outweighs the mere provision of explanatory content [2, 15].

Perceived algorithmic fairness significantly mediates the association between explanation depth and user responses. Detailed explanations do not directly shift purchase intention or brand attitude; instead, they raise users' perception of procedural fairness, which in turn improves consumer reactions. When users find the recommendation logic transparent and reasonable, they are more likely to view the recommender system as a trustworthy decision aid rather than a tool deployed solely in the platform's interest, and they become more willing to engage with the recommendations and to form a more favorable view of the brand.

The "fairness → control" path was confirmed, and the sequential pathway of detailed explanation-fairness-control-outcome obtained empirical support. Perceived control is not activated directly by the explanation itself; it builds on users' prior judgment that the procedure is fair. In other words, only when the system is seen as transparent and trustworthy do users develop a sense of engagement and agency.

Explanation depth exerted no direct impact on perceived control, and the independent mediation pathway via perceived control failed to gain empirical support. Disclosure alone is therefore insufficient to instill a sense of control. In line with self-determination theory, perceived control rests

not only on informational comprehension but also on actual scope for action and choice [16]. Compared with explanation per se, interactive features such as preference adjustment, feedback mechanisms, and privacy controls are likely to be more effective in fostering user autonomy.

5.2. Theoretical contributions and practical implications

This study makes three theoretical contributions. First, it shows that the effectiveness of algorithm explanations varies markedly with information density, enriching existing research insights into the valid boundary conditions of explanatory effects. Second, it clarifies the cognitive transmission pathway between explanation depth and user feedback, empirically bridging procedural justice theory and self-determination theory. Third, by incorporating brand attitude into the algorithm-explanation framework, it demonstrates that algorithmic transparency affects not only immediate behavioral responses but also longer-term brand cognition and evaluation.

First, platforms should prioritize providing more informative, detailed recommendation explanations. Compared with simple source cues, explanations that reveal underlying algorithmic logic and supporting data are more effective in enhancing users' perceptions of fairness and trust.

Second, beyond transparency design, platforms should strengthen mechanisms that support user autonomy. Because perceived control does not emerge from disclosure alone, platforms should also provide preference setting options, feedback entrances, and privacy control tools to boost user engagement.

Third, algorithmic transparency should be treated as part of brand management and user-relationship building. The findings indicate that transparent explanations influence not only immediate purchase responses but also brand attitudes and platform trust.

6. Conclusion

This study, based on a single-factor three-level between-subjects experiment with 240 adult consumers experienced in online shopping, develops and tests a serial dual-mediation model—anchored in procedural justice theory and self-determination theory—in which perceived algorithmic fairness and perceived control jointly transmit the effect of algorithm explanation detail on purchase intention and brand attitude. The results identify an information density threshold regarding algorithm explanation effects: only sufficiently detailed explanations significantly enhance perceived algorithmic fairness. Perceived algorithmic fairness plays a pivotal mediating role between explanations and consumer response, with detailed explanations shaping purchase intention and brand attitude primarily through fairness perceptions rather than directly. The serial path "detailed explanation → fairness → control → consumer response" is also supported, suggesting perceived control cannot be directly triggered by explanations but derives from users' prior procedural fairness evaluation. These findings provide empirical guidance for optimizing recommendation-explanation design and algorithmic-transparency governance.

Several limitations should be noted. First, the single-shot scenario design constrains external validity; future work could employ longitudinal designs or field experiments in real platforms. Second, the three stimulus conditions were not strictly matched on text length, leaving a potential confound between information richness and textual volume; subsequent studies could use materials of equal length but varying information density. Third, the model was estimated on cross-sectional data from a single time point, so the causal direction of the serial mediation should be interpreted with caution and verified with multi-wave designs. Fourth, the sample skewed toward younger, middle- to lower-spending online shoppers, the generalizability of these findings to elderly users,

high-consumption groups and users with limited digital literacy, as well as high-risk algorithmic scenarios including finance and healthcare, requires further exploration. Future research on explainable recommendations could fruitfully proceed in three directions: incorporating individual-difference variables to delineate the boundary conditions of explanation effects; using physiological measures and behavioral logs to capture users' real-time cognitive and affective responses; and embedding algorithm explanations within a broader "transparency–autonomy" co-governance framework, moving the field from effect verification toward systems-level design.

References

- [1] Zhang, Y., & Chen, X. (2020) Explainable recommendation: A survey and new perspectives. *Foundations and Trends® in Information Retrieval*, 14: 1–101.
- [2] Shin, D. (2021) The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human–Computer Studies*, 146: 102551.
- [3] Araujo, T., Helberger, N., Kruijemeier, S., & de Vreese, C. H. (2020) In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society*, 35: 611–623.
- [4] Wang, W., & Benbasat, I. (2007) Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems*, 23: 217–246.
- [5] Chatti, M. A., Guesmi, M., Vorgerd, L., et al. (2022) Is more always better? The effects of personal characteristics and level of detail on the perception of explanations in a recommender system. In *Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization*, 254–264.
- [6] Juijn, G., Stoimenova, N., Reis, J., & Nguyen, D. (2023) Perceived algorithmic fairness using organizational justice theory: An empirical case study on algorithmic hiring. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*, . 775–785.
- [7] Ajzen, I. (2002) Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology*, 32: 665–683.
- [8] Leventhal, G. S. (1980) What should be done with equity theory? New approaches to the study of fairness in social relationships. In *Social Exchange: Advances in Theory and Research*, 27–55.
- [9] Ajzen, I. (1991) The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50: 179–211.
- [10] Low, G. S., & Lamb, C. W. (2000) The measurement and dimensionality of brand associations. *Journal of Product & Brand Management*, 9: 350–370.
- [11] Lee, M. K. (2018) Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, 5: 2053951718756684.
- [12] Knijnenburg, B. P., Bostandjiev, S., O'Donovan, J., & Kobsa, A. (2012) Inspectability and control in social recommenders. In *Proceedings of the Sixth ACM Conference on Recommender Systems*, 43–50.
- [13] Wang, R., Harper, F. M., & Zhu, H. (2020) Factors influencing perceived fairness in algorithmic decision-making: Algorithm outcomes, development procedures, and individual differences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–15.
- [14] Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018) Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, 64: 1155–1170.
- [15] Binns, R., Van Kleek, M., Veale, M., Lyngs, U., Zhao, J., & Shadbolt, N. (2018) "It's reducing a human being to a percentage": Perceptions of justice in algorithmic decisions. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–14.
- [16] Deci, E. L., & Ryan, R. M. (2000) The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, 11: 227–268.