Understanding the Role of Fairness in User Adoption via Structural Equation Modeling

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Abstract

This study investigates the role of fairness in the acceptance and use of two-sided recommender systems, using video sharing platform TikTok as a case study. Through an online survey of 429 participants, we collected data on various aspects of users' perceptions and usage habits of TikTok, including system and service quality, perceived fairness, perceived usefulness, and perceived ease of use. Our findings show that system quality had a positive and statistically significant influence on perceived fairness, while service quality did not have a significant impact. Additionally perceived fairness had a statistically significant on perceived usefulness. However, the relationship between perceived fairness and attitude towards use was not statistically significant. While the fit indices for our models were not ideal, these results provide insights into the complexity of the relationships between fairness and other factors that influence user behavior in the adoption and use of two-sided recommender systems.

1. Introduction

Two-sided recommender systems (2SRS) are platforms that invite providers to create offerings on the platform, which are then recommend to consumers to satisfy their needs. The two sides refer to producers, who create and offer products or services, and consumers, who receive recommendations on these offerings by the platform. This unique structure presents challenges and opportunities for both sides. An example of a 2SRS is a short-video recommendation platform, such as TikTok, where content creators upload videos, and the platform distributes them to consumers based on their perceived interests and preferences.

The topic of fairness in 2SRS is an important area of research, as the recommendations made by these platforms can have consequences for all participants involved, impacting both the success of producers and the satisfaction of consumers. There are various ways to classify fairness in 2SRS systems, but the concept broadly refers to the equitable treatment of both producers and consumers in the system.

Examples of classifications include multi-sided fairness (which includes consumer fairness, provider fairness, and combined consumer and provider fairness) [6] and egalitarian fairness (which includes group fairness and individual fairness) [7]. In this study, we focused on examining perceived fairness to consumers on TikTok. Specifically, we wanted to investigate whether system and service quality influence perceived fairness and what effect perceived fairness has on users' perceptions of TikTok, which ultimately affects their intentions to continue using TikTok in the future.

To quantify this impact, we examined the Technology Acceptance Model (TAM), which posits that perceived usefulness and perceived ease of use are factors which influence the adoption and usage of technology. We chose to incorporate these constructs into our study, as well as web quality factors system and service quality, as suggested by Ahn et al. [7] to more fully investigate the factors that may shape users' perceptions and behavior on TikTok. In addition, we included fairness as a central construct of interest. To measure these seven constructs, we developed a set of 45 survey questions. Responses were collected from participants on MTurk. Our hypotheses concerning the causal relationships between these factors were informed by both the original TAM and the web quality extension proposed by Ahn et al [7]. By examining these relations, we hope to contribute to the larger body of research on fairness in two-sided recommender systems, which may inform the design and management of these platforms.

2. Literature Review

Here, we aim to provide the context and background information that sets the stage for our study.

2.1 Fairness

To provide context for our study, we first define fairness in the context of recommender systems and summarize the current state of research on this topic. Fairness in recommender systems refers to the equitable treatment of different stakeholders which include consumers and providers. Recommender systems, which use machine learning techniques to provide personalized recommendations based on user interests and behaviors, can suffer from various unfairness issues that can harm multiple stakeholders, such as racial or gender discrimination in job recommendations [7]. The complexity of fairness is further compounded by the personalization objective of recommender systems because user preferences observed by the system may contain biases [5]. To address these issues, research on fairness in recommendation has focused on four main areas: taxonomy, techniques, datasets, and open challenges [7]. "Taxonomy" refers to the systematic classification of fairness notions in recommendation. For example, Burke proposes a taxonomy of classes of fairness-aware recommender systems – systems distinguished by consumer fairness, provider fairness, or both [6]. "Techniques" refer to the methods used to achieve fairness in recommender systems. "Datasets" refer to the availability and quality of data used to evaluate and compare fairness in recommendations. “Open challenges” refer to challenges that arise when promoting fairness in recommendation, such as the need to balance multiple goals and consider long-term benefits in dynamic systems [7].

2.2 Technology Acceptance Model

The technology acceptance model (TAM) is a widely used theory in the field of information systems that explains how users come to accept and use a technology. TAM suggests that users' decisions about how and when to use a technology are influenced by two factors: perceived usefulness, which is the degree to which a person believes that using a particular system would help them achieve their goals, and perceived ease-of-use, which is the degree to which a person believes that using a particular system would be easy to use.

2.2.1 Extensions to TAM

Moon and Kim [4], extended upon the original TAM by Davis [3] by including playfulness as a construct. Playfulness was found to have a significant impact on attitude towards use and behavioral intentions. The addition of this construct allowed it to be more applicable to the context of the world wide web. In a study of online retailing, Ahn et al. further extended upon this model by investigating the effects of both playfulness and web quality factors on user acceptance behavior [7]. Their study found that web quality, categorized into system, information, and service quality, had a significant impact on perceived ease of use, playfulness, and usefulness, which encouraged website use in the context of online retailing. System quality refers to the characteristics of a technology that make it effective and efficient in meeting the needs of its users. It includes factors such as technical adequacy, appearance, delay, navigation, security, and privacy. Service quality, on the other hand, refers to the degree to which a technology meets the needs and expectations of its customers. It can be measured by factors such as tangibles, reliability, responsiveness, assurance, and empathy.

3. Methods

3.1 FAIR Model

Our model, named the FAIR model, is based off the original TAM model. In addition to the variables included in the original TAM model, we utilized the web quality constructs of system and service quality from Ahn et al. [7]. We elected to include the construct of information quality within the scope of service quality. The reason for this is because TikTok is predominantly an entertainment platform rather than a source of information. As such, the construct of “information quality” may not hold significant relevance to this study. That said, the question of accuracy and reliability of information found on TikTok is an important one. But as it pertains to the quality of the recommended content, it can fall under the purview of service quality. Additionally, we included the construct of perceived fairness. As such, the FAIR model includes seven latent variables: system quality, service quality,

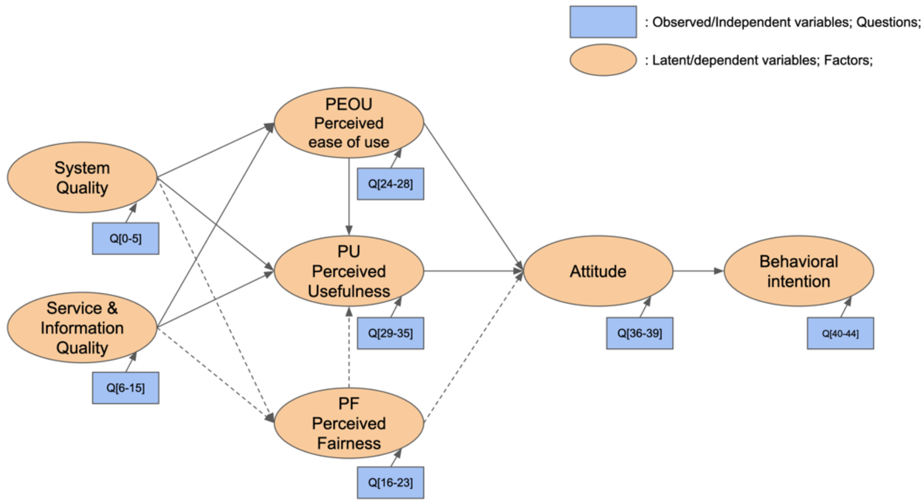

Figure 1.1. FAIR Model
Dashed lines represent the relationships of particular interest, specifically relationships between a construct and perceived fairness, the main construct of interest in this study. Solid lines represent relationships that have been established in previous literature.

perceived fairness, perceived ease of use, perceived usefulness, attitude towards use, and behavioral intentions. Causal predictions are shown in Figure 1.1. We hypothesized that all causation relations between latent variables would be statistically significant and represented by positive regression coefficients.

3.1.1 Hypotheses

The inclusion of the construct of perceived fairness in our model is unique. As such, we propose the following hypotheses regarding its relation to other constructs.

Hypothesis 1. System quality has a positive effect on perceived fairness.

Hypothesis 2. Service quality has a positive effect on perceived fairness.

Reasoning: Good system and service quality can be seen as indicators of the platform's commitment to providing a positive experience, which may include treating its users fairly.

Hypothesis 3. Perceived fairness has a positive effect on perceived usefulness.

Reasoning: Fair treatment can increase users' trust in the platform and belief that it is accurate and reliable, leading them to believe that it will be more useful for their needs.

Hypothesis 4. Perceived fairness has a positive effect on attitude towards use.

Reasoning: Feeling treated fairly can increase users' satisfaction with the platform, leading to a more positive overall attitude towards it.

The original Technology Acceptance Model (TAM) proposed that perceived ease of use and perceived usefulness were two key factors influencing users' attitudes towards using a technology and their behavioral intentions to use it [3]. In addition, Ahn et al. extended TAM by adding the constructs of system and service quality and found that these factors had positive effects on perceived ease of use and perceived usefulness [7]. Based on these previous research findings, we propose the following remaining hypotheses:

Hypothesis 5. System quality has a positive effect on perceived ease of use.

Hypothesis 6. Service quality has a positive effect on perceived ease of use.

Hypothesis 7. System quality has a positive effect on perceived usefulness.

Hypothesis 8. Service quality has a positive effect on perceived usefulness.

Hypothesis 9. Perceived ease of use has a positive effect on perceived usefulness.

Hypothesis 10. Perceived ease of use has a positive effect on attitude towards use.

Hypothesis 11. Perceived usefulness has a positive effect on attitude towards use.

Hypothesis 12. Attitude towards use has a positive effect on behavioral intentions.

3.1.2 Modified FAIR Model

We created a second model in which we combined the constructs of perceived ease of use and perceived usefulness into a single construct, which we labeled “perceived effectiveness” (PE). The name was chosen to capture the idea that the user's overall evaluation of the system is based on both how easy it is to use and how useful they perceive it to be. This decision was made for a few reasons. First, by reducing the number of model parameters, we were able to increase the EPV (events per variable), which would ideally improve the statistical power of our model. Second, this could potentially reduce issues of multicollinearity between these two constructs. Finally, we wanted to test whether the combined construct would have a stronger effect on users' attitude towards use than either perceived ease of use or perceived usefulness alone. The modified FAIR model is shown in Figure 1.2.

3.2 Survey

To collect data for this study, we administered an online survey consisting of 45 questions measuring 7 latent variables. All questions were answered using a 1–5 Likert-type scale, with 1 representing “strongly disagree” and 5 representing “strongly agree.” There was no missing data in the sample because participants were not able to submit their responses unless all questions were answered.

The survey was conducted using the platform MTurk, and initially yielded 630 responses over the course of 17 days from 15

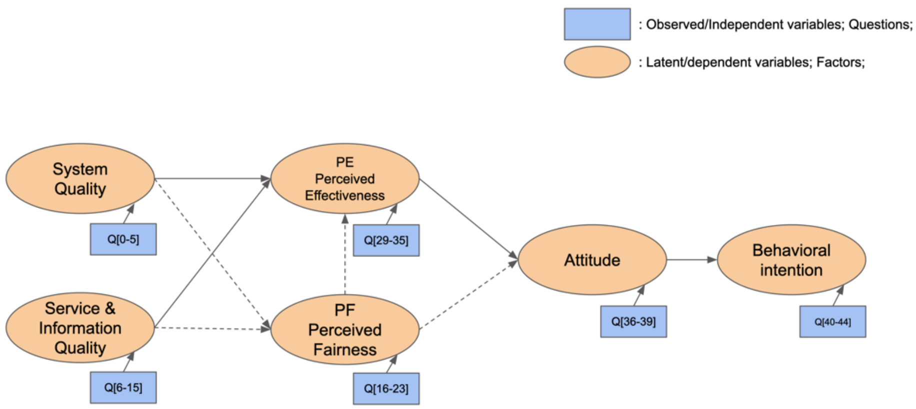

Figure 1.2. Modified FAIR Model
The same conventions for lines are used in this figure as in Figure 1.1.

November to 2 December 2023. To further ensure the reliability and validity of responses, the survey included seven reverse-worded (RW) questions, which were phrased in the opposite direction of a corresponding positive-worded (PW) question. For example, the PW question "I will keep using TikTok in the future" would be paired with the RW question "I don't intend to use TikTok in the future." RW questions serve to reduce or eliminate acquiescence bias, where respondents tend to agree with a given item regardless of its content. In addition, RW questions also serve as a quality check, as responses that conflict with their corresponding PW questions may indicate a lack of care or attention on the part of the respondent.

To ensure the quality of our data, we filtered out survey responses in which the respondent gave conflicting answers to more than two pairs of PW and RW questions. This left us with a final sample of 429 responses.

3.2.2 Demographics

After filtering, the respondents of the survey were mostly between the ages of 25 and 44. There was a roughly even split between male and female respondents. The majority of respondents identified as office workers, with a small percentage being students or independent workers. All respondents were native or fluent English speakers and had used TikTok for over 6 months. In terms of frequency of use, the majority of respondents used TikTok for more than 2 hours per day.

Detailed descriptive demographics of the respondents are shown in Table 1.

Table 1
Profile of respondents

Measure	Item	Frequency	Percentage (%)
Total		429	100
Gender	Male	213	49.7
	Female	216	50.3
Age	18-24	21	4.9
	25-34	198	46.2
	35-44	132	30.8
	45-54	51	11.9
	55-65	27	6.3
Language	Native	394	91.8
	Fluent	35	8.2
Occupation	Office worker	378	88.1
	Student	6	1.4
	Independent	28	6.5
	Retired	1	0.2
	Other	16	3.8
Experience	Over 6 months of usage	429	100
Frequency	Less than 30 mins	8	1.9
	Less than 1 hour	31	7.2
	About 1-2 hours	128	29.8
	Longer than 2 hours	262	61.1

3.3 Internal Validity/Filtering Questions

In this study, we faced several challenges when deciding which questions to retain for each latent variable in our model. Using all 45 questions from the survey would not have been possible, as we faced issues with multicollinearity among latent variables when designing our measurement model. Additionally, some questions did not show good internal validity with their associated construct. As such, it was necessary to drop some questions to create a model that was both statistically and practically meaningful.

Initially, we prioritized internal validity and attempted to retain combinations of questions that maximized the Cronbach alpha of each construct. However, the measurement model still faced issues with multicollinearity and the FAIR path model failed to converge. We then tried removing the minimum number of questions necessary to achieve a Cronbach alpha above 0.6 for each construct. We again faced issues with multicollinearity in the measurement model and the optimizer failing to find a solution for the path model.

To address these issues, we employed exploratory factor analysis (EFA) in an attempt to redistribute the questions to new or similar factors. However, the EFA results were not helpful. Specifically, the factor models resulting from EFA were not intuitive, with many questions being assigned to factors in groups that did not have a clear theme or were not meaningfully related.

We repeated all previous steps with constructs from the modified FAIR model. In this case, the only change was that questions from perceived ease of use and perceived usefulness were associated with a single construct perceived effectiveness. We again faced the same results.

In the end, the subset of questions chosen for each construct had relatively weak internal validity. See Table 2.1 and 2.2 for interval validity metrics of constructs in the original and modified FAIR model respectively. However, the questions selected allowed both the FAIR and modified FAIR path models converge and have statistically significant (low p-value) regression coefficients, which at least provided some insight into the relationships between some latent variables. The final set of questions used is shown in the appendix.

4. Results

The results of the fit indices indicated that both models did not fit the data well. While the values of the fit indices approached the recommended cut-off values for several measures, they did not reach them, suggesting that the models may not accurately represent the relationships between the variables in the study. Fit indices are shown in Table 3.1 and 3.2 for the original and modified FAIR model respectively.

Of the 12 causal relations predicted in the FAIR model, 5 were found to be statistically significant. System quality was found to have a positive and statistically significant influence ($\beta = 0.302, p < 0.1$) on perceived fairness. Service quality did not appear to have a statistically significant ($\beta = 0.102, p = 0.552$) influence on perceived fairness. Both system and service quality had a positive and statistically significant influence on perceived ease of use ($\beta = 0.935, p < 0.1$ and $\beta = 1.266, p < 0.1$ respectively), consistent with the predictions developed from the extended model of Ahn et. al. See Figure 2.1 for statistically significant relations in the original FAIR model.

Table 2.1
Test results of internal reliability and convergent validity (FAIR model)

Construct	Items	Internal reliability		Convergent validity		
		Cronbach alpha	Item-total correlation	Factor loading	Composite reliability	Variance extracted
System quality	5	0.668	0.394	0.337	0.665	0.297
			0.469	0.480		
			0.461	0.595		
			0.383	0.376		
			0.440	0.484		
Service quality	5	0.430	0.388	0.485	0.509	0.171
			0.142	0.258		
			0.338	0.492		
			0.311	0.448		
			0.047	0.212		
Perceived fairness	5	0.601	0.025	-0.013	0.667	0.381
			0.230	0.186		
			0.566	0.852		
			0.533	0.703		
			0.513	0.641		
Perceived ease of use	4	0.699	0.410	0.206	0.703	0.371
			0.560	0.248		
			0.455	0.220		
			0.510	0.242		
Perceived usefulness	4	0.660	0.549	0.161	0.675	0.339
			0.372	0.114		
			0.391	0.142		
			0.459	0.145		
Attitude toward use	2	0.481	-	0.282	0.465	0.309
				0.229		
Behavioral intentions	2	0.516	-	0.228	0.520	0.353
				0.190		

The regression coefficients representing the influence of system and service quality on perceived usefulness were both positive, but the p-values were too large ($\beta = 1.197, p = 0.122$ and $\beta = 0.795, p = 0.335$ respectively) to establish a causal relationship. The same was found for perceived ease of use ($\beta = 0.527, p = 0.167$). On the other hand,

Table 2.2
Test results of internal reliability and convergent validity (modified FAIR model)

Construct	Items	Internal reliability		Convergent validity		
		Cronbach alpha	Item-total correlation	Factor loading	Composite reliability	Variance extracted
System quality	5	0.668	0.394	0.336	0.664	0.297
			0.469	0.481		
			0.461	0.594		
			0.383	0.379		
			0.440	0.483		
Service quality	5	0.430	0.388	0.484	0.509	0.170
			0.142	0.259		
			0.338	0.490		
			0.311	0.448		
			0.047	0.213		
Perceived fairness	5	0.601	0.025	-0.011	0.668	0.381
			0.230	0.184		
			0.566	0.850		
			0.533	0.699		
			0.513	0.641		
Perceived effectiveness	8	0.798	0.495	0.155	0.804	0.337
			0.566	0.176		
			0.462	0.157		
			0.568	0.177		
			0.572	0.169		
			0.381	0.120		
			0.480	0.153		
			0.544	0.155		
Attitude toward use	2	0.481	-	0.282	0.464	0.308
				0.228		
Behavioral intentions	2	0.516	-	0.224	0.520	0.353
				0.187		

perceived fairness had a positive and statistically significant ($\beta = 0.301, p < 0.1$) influence on perceived usefulness, supporting hypothesis 3.

We were unable to find statistically significant influences from perceived fairness ($\beta = 0.033, p = 0.796$), perceived ease of use

Table 3.1

Fit indices of the FAIR model

Fit index	Scores	Recommended cut-off values
Absolute fit measures		
Minimum fit function chi-square ($\mathcal{X}^2$)	642.241	The lower, the better
Degrees of freedom (d.f.)	311	
$\mathcal{X}^2$/d.f.	2.065	<5
Root mean square residual (RMSR)	0.079	<0.05
Incremental fit measures		
Tucker-Lewis index (TLI)	0.844	>0.90
Comparative Fit Index (CFI)	0.862	>0.90

($\beta = 0.386, p = 0.178$), or perceived usefulness ($\beta = 0.302, p = 0.155$) on attitude towards use. However, attitude towards use was found to have a positive and statistically significant ($\beta = 1.311, p < 0.1$) influence on behavioral intentions, consistent with the predictions of the TAM model.

We found similar results in the modified FAIR model (see Figure 2.2). System quality and service quality had positive and statistically significant effects on perceived effectiveness ($\beta = 1.472, p < 0.01$ and $\beta = 1.564, p < 0.1$ respectively), while perceived fairness did not have a statistically significant effect on perceived effectiveness ($\beta = 0.071, p = 0.577$).

Like the original FAIR model, perceived fairness was not found to have a statistically significant effect on attitude towards use ($\beta = -0.016, p = 0.884$). On the other hand, perceived effectiveness did have a statistically significant effect on attitude towards use ($\beta = 0.602, p < 0.01$).

5. Discussion

Our study found that system quality had a positive and statistically significant influence on perceived fairness. However, the relationship between service quality and perceived fairness was not statistically significant. Both system and service quality had a positive and statistically significant influence on perceived ease of use, which is in line with the original TAM model. The other relationships we investigated, including those between perceived fairness, perceived ease of use, and perceived usefulness on attitude towards use, were not statistically significant.

Overall, our results suggest that fairness may play a role in the acceptance and use of 2SRS, but our models were not able to fully capture this relationship.

Table 3.2
Fit indices of the modified FAIR model

Fit index	Scores	Recommended cut-off values
Absolute fit measures		
Minimum fit function chi-square ($\mathcal{X}^2$)	817.820	The lower, the better
Degrees of freedom (d.f.)	315	
$\mathcal{X}^2$/d.f.	2.596	<5
Root mean square residual (RMSR)	0.079	<0.05
Incremental fit measures		
Tucker-Lewis index (TLI)	0.844	>0.90
Comparative Fit Index (CFI)	0.860	>0.90

5.1 Limitations

The following potential limitations should be considered when interpreting the findings of this study.

5.1.1 Sample size

It is likely that the sample size of 429 may not accurately represent the characteristics and behaviors of TikTok's user base, which includes approximately 30 million daily active users on iOS alone [2]. The sample size alone may have been too small to detect some of the hypothesized relationships between the constructs in our model.

5.1.2 Sample bias

The majority of survey respondents were between the ages of 25 and 44, while TikTok is known to be popular among younger generations [1].

5.1.3 Data quality

The fact that a significant portion of the responses were dropped due to conflicting answers to reverse-worded questions raises concerns about the quality of the responses and potential impact on the reliability of the results.

5.1.4 Applicability of TAM

Another possible limitation of our study is that we used the Technology Acceptance Model (TAM) as a basis for our models. TAM was initially developed to study the adoption of corporate information technologies by workers and has been primarily tested in that context. The constructs of system and service quality, which we adapted from Ahn et. al, were originally introduced in the context of web-based online retailing. It is uncertain to what extent these constructs and the TAM model are applicable to the specific context of TikTok, which, as a short video sharing platform made for entertainment, differs significantly from traditional corporate or online retailing contexts. It would be beneficial to initially evaluate the

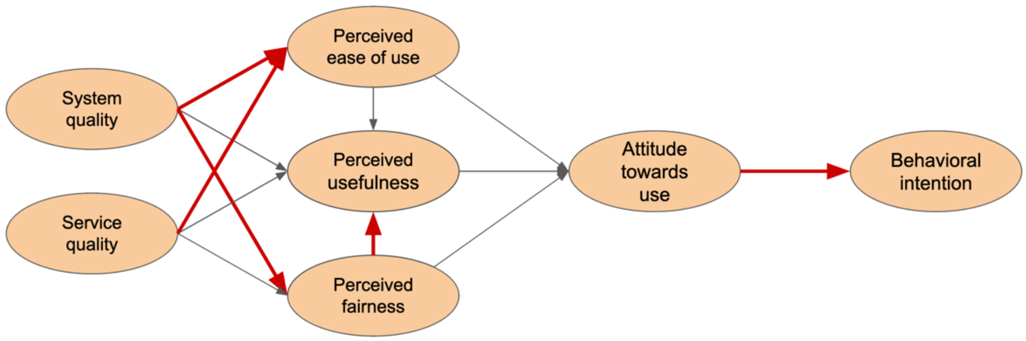

Figure 2.1. Statistically significant relations in the FAIR model
Statistically significant relations are shown in red.

applicability of TAM as a foundation for our models by determining the compatibility of the data with TAM alone, prior to incorporating the construct of fairness into the analysis.

Other possible explanations for our failure to find a strong model is issues with the specific wording of the survey questions, or the fact that the latent variables in our models may not accurately capture the interaction of fairness with other factors that influence user behavior.

6. Conclusion

In this study, we set out to investigate the role of fairness in the acceptance and use of 2SRS, using TikTok as a case study. We conducted an online survey and used TAM-inspired models to understand user behavior in the adoption and use of such systems. Our models included the construct of perceived fairness, which we hypothesized would be both positively influenced by and have a positive influence on the other latent variables in our models.

Our models were not able to fully capture the relationship between fairness and the acceptance and use of 2SRS. It should be noted that the internal validity of our constructs was generally poor, so any statistically significant causal relations between our constructs identified by our model should be interpreted with caution. Our findings suggest that system quality may be an important factor in influencing users' perceptions of fairness. This suggests that platform developers and designers should prioritize ensuring high system quality to enhance users' perceptions of fairness and potentially increase acceptance and use of the platform. Additionally, our finding that service quality did not have a statistically significant influence on perceived fairness suggests that it may not be as crucial in influencing users' perceptions of fairness. This could potentially be useful for platform developers to consider when allocating resources for improving different aspects of the platform. Finally, the finding that perceived fairness had a statistically significant influence on perceived usefulness, suggests that fairness should be considered, if not prioritized, in the design and management of a platform,

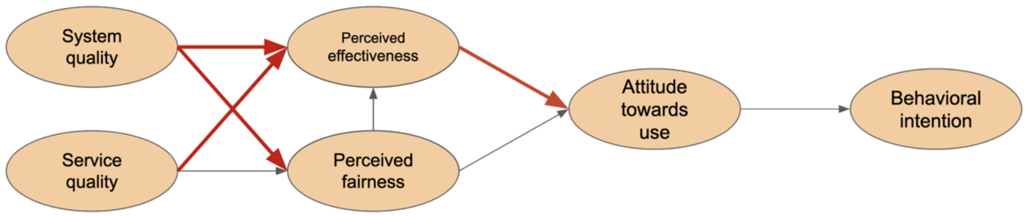

Figure 2.2. Statistically significant relations in the modified FAIR model
Statistically significant relations are shown in red.

as it may have downstream effects on other factors that influence users' behaviors and attitudes towards the platform.

Future research could aim to use larger sample sizes and newer measurement models. We could refine the latent variable constructs to better understand the adoption and usage of social media platforms which use 2SRS. It is also worth noting that our models were not able to capture the relationship between perceived fairness and attitude towards use. This suggests that there may be other factors at play in these relationships, and further research is needed to fully understand the role of fairness in the acceptance and use of 2SRS.

Appendix

This section contains the questions used in the survey. Respondents were asked to mark their answer to each of the questions using the 1–5 Likert scales on which the anchor for 1 was "strongly disagree" and for 5 "strongly agree".

Questions 2, 7, 9, 25, 31, 37, 42 are reverse-worded questions. They are associated with positive-worded questions 1, 6, 8, 24, 30, 36, 41 respectively. Question 15 is a reverse-worded question not associated with any positive-worded question. Responses to reverse-worded questions were studied with inverted Likert scales so that they measured their associated construct in the same direction as positive-worded questions.

Questions which were excluded from the path analysis are formatted in strikethrough. It is important to note that the removal of these questions was not a result of their detrimental effect on internal validity. In fact, a substantial number of these questions accurately represented their respective constructs. They were removed to enable the model to converge and generate valid regression analyses between constructs.

System quality

0. TikTok has an appropriate style of design for site type.
1. It's easy to navigate on TikTok to find what I want.
2. TikTok has an unclear app navigation.
3. TikTok has a fast response time.
4. ~~TikTok keeps personal information (age, address, name ...) that I provided secure from exposure.~~
5. TikTok creates an enjoyable audio-visual experience.

Service (and information) quality

6. ~~The recommended items correspond to my needs and preferences.~~
7. ~~TikTok wrongly infers my interests.~~
8. The recommended items cover a variety of topics.
9. ~~TikTok recommended items are repetitive.~~
10. ~~TikTok provides reliable information.~~
11. The recommended items are novel.
12. ~~I can easily change the way TikTok recommends content to me.~~
13. The recommended items adapt to my changing taste and preferences.
14. TikTok recommends me content based on inferred information, such as gender, location, profession, etc.
15. TikTok displays too many advertisements.

Perceived fairness

16. The content from TikTok controls my preferences and taste.
17. The content recommended to me is populated by trending videos.
18. ~~My age doesn't limit the content recommended to me.~~
19. ~~My gender doesn't limit the content recommended to me.~~
20. My race doesn't limit the content recommended to me.
21. My religion doesn't limit the content recommended to me.
22. ~~My location doesn't limit the content recommended to me.~~
23. My social connections don't limit the content recommended to me.

Perceived ease of use

24. It is easy for me to become skillful at using TikTok.
25. ~~Using TikTok requires a lot of mental effort.~~
26. It is easy for me to change my preferences in TikTok.
27. It is easy to get TikTok to do what I want it to do.
28. TikTok is user friendly.

Perceived usefulness

29. ~~When using TikTok, I do not realize the time elapsed.~~
30. TikTok gives me enjoyment and keeps me entertained.
31. ~~Using TikTok is dull and boring.~~
32. TikTok stimulates my curiosity.
33. TikTok keeps me informed of the latest trends.
34. TikTok leads me to explore new content.
35. ~~TikTok updates me about my friends' lives.~~

Attitude toward use

36. Using TikTok is a good idea.
37. ~~Using TikTok is a bad idea.~~
38. ~~Using TikTok is a positive idea.~~
39. Using TikTok is a wise idea.

Behavioral intention to use

40. ~~I will keep using TikTok in the future.~~
41. I will use TikTok on a regular basis in the future.
42. I don't intend to use TikTok in the future.
43. ~~I will use this site rather than other platforms, for example, YouTube, Instagram, or Facebook.~~
44. ~~I will recommend TikTok to others.~~

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