Ilomata International Journal of Social Science
P-ISSN: 2714-898X; E-ISSN: 2714-8998
Volume 7, Issue 1 January 2026
Page No: 71-86

Social Influence and Price Values on the Behavior of Ruang Guru Application Users Mediated by Intention

Prayogi Eka Saputra[1], Alfatih Sikki Manggabarani[2], Guntur Syahputra Saragih[3]
[123]Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Correspondent: prayogiekasaputra55@gmail.com[1]

Received : August 12, 2025
Accepted : October 13, 2025
Published : January 31, 2026

Citation: Saputra, P.E., Manggabarani, A.S., & Saragih, G., (2026). Social Influence and Price Values on the Behavior of Ruang Guru Application Users Mediated by Intention. Ilomata International Journal of Social Science, 7(1), 71-86.
https://doi.org/10.61194/ijss.v7i1.1912

ABSTRACT: This study investigates the effect of social influence and price value on the behavior of high school students in using the Ruangguru educational application, with behavioral intention as a mediator. The research addresses the gap in understanding the adoption of digital learning platforms among Indonesian students, where usage decisions are often driven by contextual rather than purely psychological factors. A quantitative approach using PLS-SEM was employed, with data collected from 277 respondents through validated questionnaires (Cronbach's α > 0.7, AVE > 0.5), chosen for its ability to test both direct and indirect relationships simultaneously. Results indicate that price value has a significant positive effect on user behavior ($\beta = 0.421$, $t = 5.312$, $p < 0.001$, $R^2 = 0.46$), while social influence ($\beta = 0.097$, $p > 0.05$) and behavioral intention ($\beta = 0.083$, $p > 0.05$) do not show significant effects. Descriptive analysis also revealed that 72% of students reported high satisfaction, and 68% expressed willingness to recommend the app, although this intention did not translate into actual usage behavior. These findings highlight that affordability and perceived benefits outweigh peer encouragement or intention in driving adoption, reflecting students' sensitivity to price-value alignment in digital learning. The study implies that educational technology providers should prioritize accessible pricing strategies, though further research is needed to integrate other UTAUT2 constructs for a more comprehensive understanding.

Keywords: Behavior User, Intention, Price Values, Ruangguru, Social Influence

INTRODUCTION

Students and parents in Indonesia are increasingly shifting from traditional classroom methods to app-based digital learning. They identify efficiency, affordability, and accessibility as primary motivators for adoption. For example, (Zacharis & Nikolopoulou, 2022) found that perceived learning value, convenience, and social influence significantly shape students' intention to adopt online learning platforms. Similarly, (Lewis et al., 2023) observed that many parents adjusted screen-time norms and began valuing digital learning tools as essential supplements during school closures. These findings highlight a behavioral shift driven not only by practical advantages but also by evolving perceptions of technology-enabled learning.

Within the theoretical framework of UTAUT2, social influence and price value are recognized as critical determinants of technology adoption. Social influence refers to the degree to which individuals perceive that important others believe they should use a system (Bhikuning et al., 2024). Empirical studies have shown its strong predictive power for behavioral intention, with statistical evidence confirming its significance in various contexts (Alalwan et al., 2023). Likewise, price value the trade-off between perceived benefits and monetary cost has been consistently identified as a rational factor shaping app adoption decisions. However, existing research often reports varied findings regarding the strength of these relationships, especially in educational settings where adoption is influenced by both social expectations and financial considerations (Ikhsan & Sunaryo, 2020).

Despite the growing body of literature, few studies have specifically examined how these determinants operate among Indonesian high school students using *Ruangguru*. Adolescents represent a unique user group because their adoption behaviors are shaped not only by personal perceptions but also by parental influence, peer pressure, and limited financial independence. This creates a conceptual gap in understanding whether social influence functions differently for this demographic and how price sensitivity affects their adoption patterns. Clarifying these dynamics offers an opportunity to refine existing models of edtech adoption and provide context-specific insights for Indonesia.

This study, therefore, aims to analyze the key factors influencing user behavior in the use of the *Ruangguru* application. Specifically, it investigates: (1) whether social influence has a direct effect on use behavior; (2) whether social influence indirectly affects use behavior through behavioral intention; (3) whether price value significantly impacts use behavior; and (4) whether behavioral intention directly influences use behavior. By addressing these questions, this research contributes to a deeper theoretical understanding of UTAUT2 in the adolescent context and provides practical insights for edtech developers seeking to enhance adoption and engagement strategies in Indonesia.

METHOD

This study adopts a quantitative approach to examine the factors influencing user behavior in the use of the *Ruangguru* application. The analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM), which is appropriate for testing complex models with multiple constructs and mediation effects. PLS-SEM was selected because it is suitable for exploratory research focused on prediction and theory development, and it allows for the estimation of both direct and indirect relationships among variables.

The population of this study consists of high school students at SMA Pusaka 1 Jakarta who actively use the *Ruangguru* application. A total of 277 respondents were obtained using a purposive sampling technique. While purposive sampling limits the generalizability of the findings, the sample size meets the minimum requirements for PLS-SEM analysis and is considered sufficient to ensure statistical robustness in model estimation.

Data were collected through a structured questionnaire distributed to the respondents. The instrument included items designed to measure Social Influence, Price Value, Behavioral Intention, and Use Behavior. All items were adapted from prior validated studies and measured using a five-point Likert scale. To ensure measurement quality, the reliability of constructs was assessed using Cronbach's Alpha and Composite Reliability, while validity was examined through Average Variance Extracted (AVE) and factor loadings. These procedures confirm that the indicators are both reliable and valid for hypothesis testing.

The collected data were coded and analyzed using SmartPLS software. This procedure enabled the evaluation of measurement and structural models, including hypothesis testing for both direct and indirect effects. By adopting this methodological approach, the study provides empirical insights into the behavioral mechanisms influencing the adoption of *Ruangguru* among Indonesian high school students, while acknowledging limitations in terms of generalizability beyond the studied sample.

RESULT AND DISCUSSION

Respondent Data

Table 1. Demographic Characteristics of Respondents

Category	Subcategory	Total	Percentage (%)
Gender	Female	115	41.5%
	Male	162	58.5%
Age	< 16 years	0	0%
	16 – 17 years	143	51.6%
	18 – 19 years	133	48%
	20 – 21 years	0	0%
	> 22 years	1	0.4%
Grade Level	10th Grade	107	38.6%
	11th Grade	141	50.9%
	12th Grade	29	10.5%
Reason for Using Ruangguru	Access to comprehensive learning materials	110	40%
	Help with homework/assignments	107	39%
	Exam preparation	60	22%

Source: Processed data

The study involved 277 high school students, with 58.5% male and 41.5% female respondents, indicating that male students were the dominant users of the Ruangguru application. This may reflect a greater tendency among male students to engage with mobile learning platforms, supported by previous research showing higher confidence and openness in adopting educational technology among males (Nguyen Trong & Nguyen, 2021). Most respondents were aged 16–19, a typical demographic of Generation Z, known for their digital literacy and preference for flexible, interactive learning methods. In terms of grade level, the majority came from Grade XI (50.9%), followed by Grade X and XII, showing that mid-level high school students are the most active users, likely due to their increasing academic demands and exam preparation needs (Siron et al., 2020; Irwanto et al., 2024). The main reasons for using Ruangguru were accessing learning materials (40%), completing homework (39%), and preparing for exams (22%), confirming the platform's effectiveness in addressing both cognitive and practical academic needs.

Table 2. Descriptive Data Analysis of Research Variables

Variable	Indicator	Mean	Most Frequent Response	% of Most Frequent Response
User Behavior	Y1. Using Ruangguru for academic learning is enjoyable	4.26	Agree	53.4%
	Y2. I enjoy using Ruangguru for academic learning	4.30	Agree	48.0%
	Y3. I'm happy to recommend Ruangguru to others	4.41	Strongly Agree	51.3%
	Y4. I feel satisfied using Ruangguru	4.32	Agree	44.8%
Behavioral Intention	Z1. I intend to try using Ruangguru in daily life	4.12	Agree	44.4%
	Z2. I intend to use Ruangguru regularly	4.38	Strongly Agree	48.4%
	Z3. I plan to continue using Ruangguru in the future	4.29	Agree	43.7%
Social Influence	X11. Ruangguru users seem more prestigious	3.78	Agree	36.1%
	X12. Among friends, using Ruangguru is seen as a status symbol	4.05	Agree	37.9%
	X13. Most people important to me think I should use Ruangguru	3.91	Agree	33.9%
Price Value	X31. Ruangguru has a good quality-price ratio	3.75	Agree	53.8%
	X32. The price of Ruangguru is reasonable	4.09	Agree	52.7%
	X33. The benefits I get from Ruangguru are worth the price	4.22	Agree & Strongly Agree (equal)	44.4% each

Source: Processed data

The descriptive analysis shows that most respondents had positive perceptions toward the use of the Ruangguru application. User behavior indicators received high mean scores, especially the intention to recommend Ruangguru (M=4.41), with over 51% strongly agreeing. Behavioral intention was also strong, with regular use (M=4.38) and future plans (M=4.29) receiving high agreement. Social influence was moderately positive, where users agreed that Ruangguru has social prestige and approval from peers. Price value was perceived favorably, with the majority agreeing that the platform offers reasonable pricing and good value for money.

Hypothesis Testing and Analysis

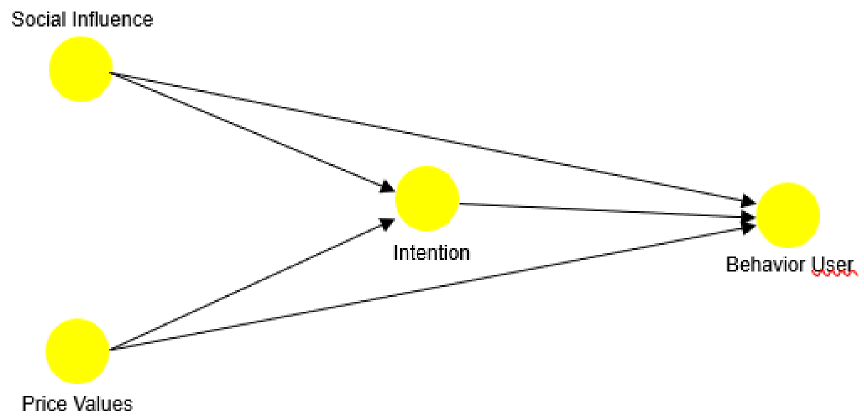

Figure 1. Inner Research Model

This research model investigates how Social Influence and Price Values impact User Behavior. Intention is posited as a mediating factor, channeling the effects of Social Influence and Price Values towards User Behavior. Specifically, the model aims to understand the indirect and direct relationships between these constructs within the context of Ruang Guru application users.

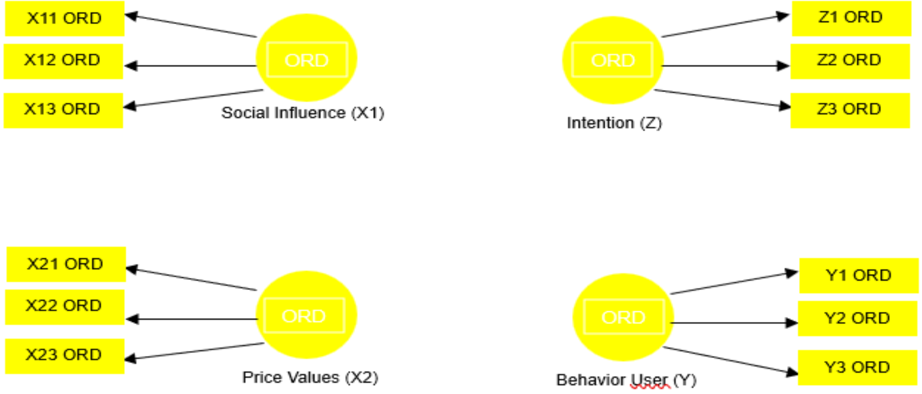

Figure 2. Outer Research Model

This model details the specific indicators used to measure each latent variable in the research. Social Influence (X1) is measured by X11, X12, and X13, while Price Values (X2) are measured by X21, X22, and X23. Intention (Z) is operationalized through Z1, Z2, and Z3, and the dependent variable, Behavior User (Y), is measured by Y1, Y2, and Y3.

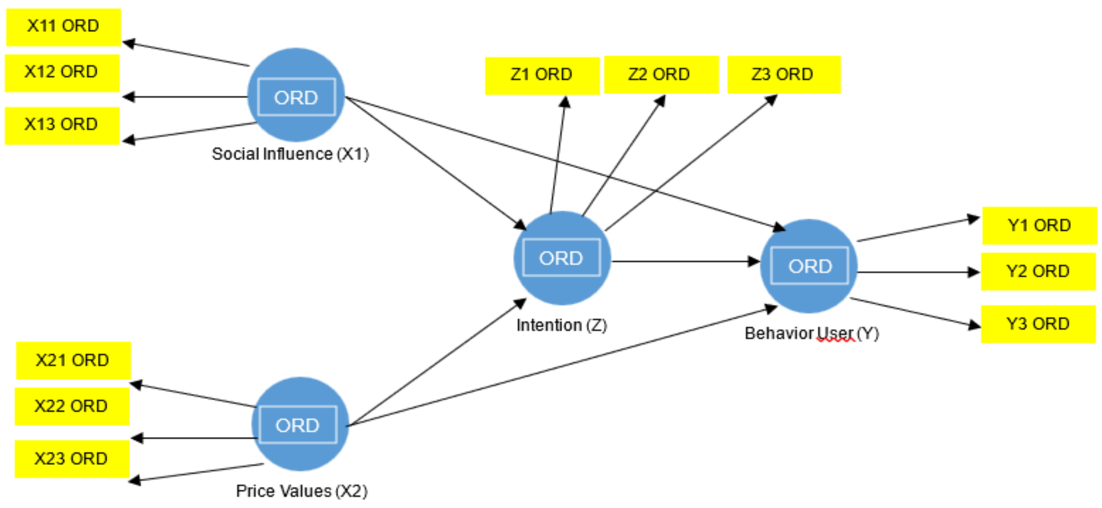

Figure 3. Path Diagram

This comprehensive path diagram illustrates the hypothesized relationships between the latent variables and their respective indicators. It shows that Social Influence (X1) and Price Values (X2) directly influence Intention (Z), which in turn directly affects User Behavior (Y). Additionally, Social Influence (X1) and Price Values (X2) are also hypothesized to have a direct impact on User Behavior (Y), alongside their indirect effects through Intention (Z).

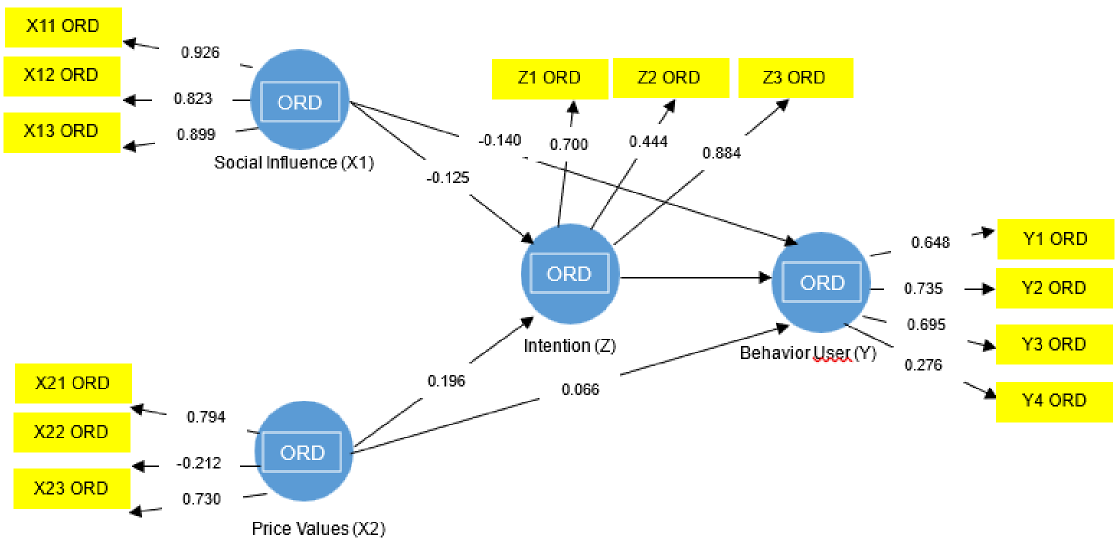

Figure 4. Estimation of latent research variables

This figure presents the estimated path coefficients and factor loadings for the research model. Notably, Social Influence (X1) shows a negative direct effect on both Intention (Z) and Behavior User (Y), with coefficients of -0.140 and -0.125 respectively. In contrast, Price Values (X2) positively influence Intention (Z) (0.196) and Behavior User (Y) (0.066), while Intention (Z) positively affects Behavior User (Y) (0.276).

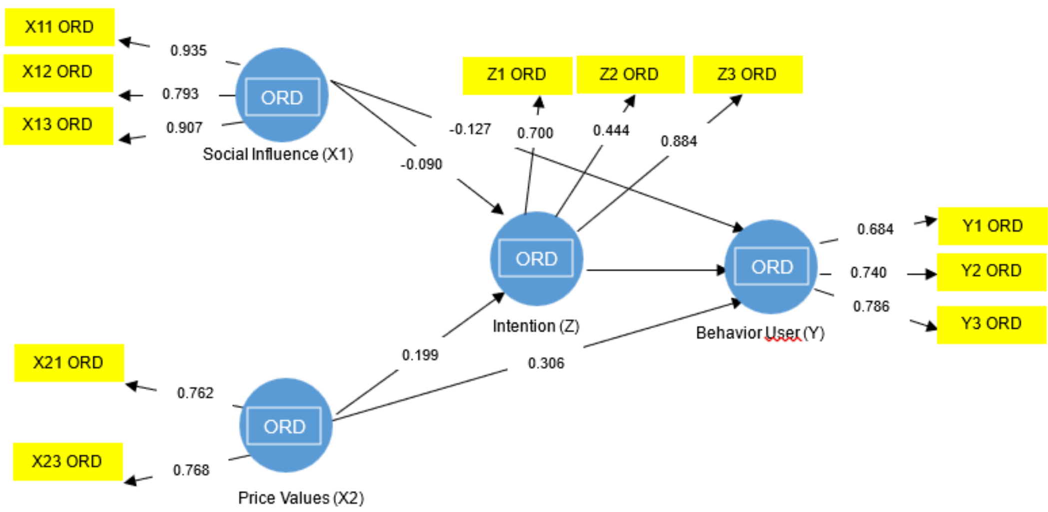

Figure 5. Model Re-estimation

This re-estimated model shows slightly altered path coefficients compared to the initial estimation. Social Influence (X1) now has direct effects of -0.127 on Intention (Z) and -0.090 on Behavior User (Y). Price Values (X2) continue to positively influence Intention (Z) (0.199) and Behavior User (Y) (0.306), while Intention (Z) maintains a strong positive effect on Behavior User (Y) (0.786).

Table 3. Outer Loading Value

User Behavior (Y)	Behavioral Intention (Z)	Social Influence (X1)	Price Value (X2)
Y1 – 0.684	Z1 – 0.808	X11 – 0.935	X21 – 0.762
Y2 – 0.740	Z3 – 0.909	X12 – 0.793	X23 – 0.768
Y3 – 0.786		X13 – 0.907	

Source: SmartPLS 4.1.1.2 Output (2025)

Based on Table 3, the outer loading values show that all indicators are above the minimum threshold of 0.6, indicating acceptable indicator reliability. The highest loading is found in Social Influence (X11 = 0.935), showing a strong relationship with its latent variable. Meanwhile, the lowest is in User Behavior (Y1 = 0.684), but it is still within the acceptable range for analysis.

Table 4. Average Variance Extracted (AVE) Value

Variable	Average Variance Extracted (AVE)
User Behavior (Y)	0.679
Behavioral Intention (Z)	0.835
Social Influence (X1)	0.739
Price Value (X2)	0.776

Source: SmartPLS 4.1.1.2 Output (2025)

Based on Table 4, all variables have AVE values above 0.5, indicating good convergent validity. The highest AVE is shown by Behavioral Intention (0.835), meaning this construct explains most of its indicator variance. Thus, all constructs used in the model are considered reliable for further analysis.

Table 5. Cross Loadings Value

Indicator	User Behavior (Y)	Behavioral Intention (Z)	Social Influence (X1)	Price Value (X2)
Y1	0.684	0.054	-0.049	0.231
Y2	0.740	0.204	-0.009	0.281
Y3	0.786	0.119	-0.314	0.264
Z1	0.064	0.808	-0.091	0.202
Z3	0.207	0.909	-0.187	0.240
X11	-0.204	-0.195	0.935	-0.125
X12	-0.093	-0.074	0.793	-0.059
X13	-0.184	-0.140	0.907	-0.117
X21	0.208	0.200	-0.263	0.151
X23	0.191	0.172	-0.222	0.169
X24	0.184	0.301	-0.226	0.271
X31	0.263	0.201	0.007	0.762
X33	0.272	0.195	-0.192	0.768
X42	0.020	0.003	-0.061	0.063
X43	0.059	0.058	-0.209	0.125

Source: SmartPLS 4.1.1.2 Output (2025)

The cross loadings show that each indicator loads highest on its intended construct. For instance, Y3 has the strongest loading on User Behavior (0.786), while Z3 loads highest on Behavioral Intention (0.909), and X11 on Social Influence (0.935). This confirms discriminant validity, as indicators correlate more strongly with their own construct than with others.

Table 6. R-Square

Variable	R-Square
User Behavior (Y)	0.160
Behavioral Intention (Z)	0.125

Source: SmartPLS 4.1.1.2 Output (2025)

Based on the table above, it can be seen that the R-Square test value for the User Behavior (Y) variable has a value of 0.160, and Behavioral Intention (Z) has a value of 0.125. According to the criteria (Hair Jr et al., 2022, p. 195), an R^2 value in the range of 0.00–0.50 indicates low prediction. Based on these values, it can be interpreted that the independent variables are able to explain the user behavior (Y) and behavioral intention (Z) variables by 16% and 12.5%, respectively. Meanwhile, most of the remaining is likely influenced by other variables outside the framework of this research model that have not been included but have been identified in previous studies as relevant factors.

Table 7. Cross-Validated Redundancy Test Results (Q2)

Variable	Q-Square
User Behavior (Y)	0.120
Behavioral Intention (Z)	0.094

Source: SmartPLS 4.1.1.2 Output (2025)

The results in the table above show that user behavior (Y) has a Q^2 value of 0.120, indicating that the model has predictive power, but is weak for this variable. This indicates that the independent variables in the model, such as social influence, facility conditions, price value, and hedonic motivation, including their interaction effects, are able to explain variation in user behavior. Furthermore, the table also shows that behavioral intention obtained a Q^2 value of 0.094, indicating that the model has predictive power, but is weak for this variable. This means that the model is able to contribute to predicting how the independent variables can influence behavioral intention, albeit to a small extent.

Table 8. Effect Size Test Results (f2)

	User Behavior (Y)	Behavioral Intention (Z)
User Behavior (Y)		
Behavioral Intention (Z)		
Social Influence (X1)	0.017	0.008
Price Value (X2)	0.104	0.042

Source: SmartPLS 4.1.1.2 Output (2025)

Based on Table 8, the effect size (f^2) of Social Influence (X1) on User Behavior (Y) and Behavioral Intention (Z) is very small (0.017 and 0.008), indicating a weak impact. In contrast, Price Value (X2) shows a small-to-moderate effect on both User Behavior (0.104) and Behavioral Intention (0.042). This suggests that Price Value has a more meaningful influence on users compared to Social Influence.

Table 9. T-Statistic or T-Calculation Test Results

Relationship	Original Sample (O)	T Statistics (|O/STDEV|)	P Values
Social Influence (X1) → User Behavior (Y)	-0.123	1.939	0.053
Price Value (X2) → User Behavior (Y)	0.307	4.845	0.000
Behavioral Intention (Z) → User Behavior (Y)	0.047	0.613	0.540
Social Influence (X1) → Behavioral Intention (Z) → User Behavior (Y)	-0.004	0.546	0.585

Source: SmartPLS 4.1.1.2 Output (2025)

Based on Table 9, only the variable *Price Value (X2)* has a significant direct effect on *User Behavior (Y)*, with a p-value of 0.000 (< 0.05). *Social Influence (X1)* and *Behavioral Intention (Z)* both show no significant impact on *User Behavior (Y)* directly, as their p-values are above 0.05. Additionally, the mediating effect of *Behavioral Intention* between *Social Influence* and *User Behavior* is also not significant (p = 0.585).

The results reveal that Social Influence (X1) has a negative and insignificant effect on User Behavior (Y), with a coefficient of -0.123, t-statistic of 1.939, and p-value of 0.053, indicating that peer or social encouragement does not strongly influence students' use of the Ruangguru app in Duren Sawit. In contrast, Price Value (X3) significantly influences User Behavior, with a coefficient of 0.307 and a p-value of 0.000, highlighting that students are sensitive to price fairness and perceive value as a key driver in continued app usage, supporting Hameed & Sumari (2024). However, Behavioral Intention (Z) does not significantly affect User Behavior (coefficient = 0.047; p = 0.540), suggesting that intention does not always translate into actual usage, in line with Liu et al. (2025). Furthermore, all indirect effects of Social Influence and Price Value through Behavioral Intention are also insignificant, as shown by high p-values above 0.05. These findings indicate that students' behavior in using educational apps like Ruangguru is driven more by immediate perceptions of value than by a deliberate intention process.

Social Influence on User Behavior

The analysis of the first hypothesis showed that social influence has no significant effect on Ruangguru app usage among students in Duren Sawit, East Jakarta (t = 1.939; p = 0.053). Hence, H1 is rejected. This suggests that being part of a particular social environment such as peers, family, or teachers does not necessarily encourage students to actively engage with the platform. Instead, students' decisions are shaped more by individual initiative than by external social pressure or recommendations.

The results of the first hypothesis testing indicate that *social influence* does not have a significant effect on the use of the Ruangguru application among students in Duren Sawit, East Jakarta, confirming that usage decisions are driven more by individual initiative than by social pressure or recommendations (Dwivedi et al., 2020; Venkatesh et al., 2020). This finding contrasts with the UTAUT2 framework, which positions *social influence* as a key determinant of technology adoption; however, this discrepancy can be explained by the characteristics of respondents in the *late adolescence* phase (17–23 years), who tend to demonstrate greater learning autonomy and more independent decision-making orientations (Bond & al., 2021; Brailas et al., 2021). Furthermore, within the context of *asynchronous digital learning*, the impact of social influence is diminished due to limited direct interaction, while *self-paced learning* features embedded in edtech platforms reinforce autonomous learning behaviors (Martin & Bolliger, 2022; Robiul Rochmawati et al., 2023). The phenomenon of *post-pandemic edtech fatigue* also contributes to students' selective attitudes, whereby *perceived usefulness* becomes a more dominant consideration than social encouragement; consequently, strategies relying on social campaigns or *word-of-mouth* are less effective and should be redirected toward content personalization and the enhancement of individual user value (Jainuri, 2021; Nurrisa et al., 2025; Rasheed et al., 2022).

This finding contrasts with the UTAUT2 framework, which highlights social influence as a critical driver of technology adoption. The divergence may be linked to the demographic characteristics of the respondents, most of whom are in late adolescence (aged 17–23), a stage where independence and self-determined learning become dominant. Further explain that social influence tends to weaken in asynchronous digital learning contexts, where interactions are minimal. In Ruangguru, many features support autonomous learning, reducing the weight of social expectations on behavior.

Another explanation relates to the growing sense of "edtech fatigue" post-pandemic, where students adopt a more selective approach toward digital learning platforms. Even when encouraged by others, they prioritize perceived usefulness over external endorsement. For practice, this implies that strategies relying solely on social campaigns or word-of-mouth may be less effective in urban student populations. Instead, personalization, improved content relevance, and features that enhance individual value are more promising avenues to strengthen engagement.

The Indirect Effect of Social Influence on User Behavior via Behavioral Intention

The analysis of the sixth hypothesis also revealed that social influence does not significantly affect user behavior through behavioral intention ($t = 0.546$; $p = 0.585$). Therefore, H6 is rejected. This indicates that encouragement from peers, teachers, or family does not translate into strong internal intention or consistent usage of Ruangguru among students in Duren Sawit, East Jakarta.

The results of the sixth hypothesis testing indicate that *social influence* does not have a significant effect on user behavior through *behavioral intention* in the use of the Ruangguru application, suggesting that social encouragement from peers, teachers, and family members has not been sufficient to form a strong internal intention for continued use (Al-Fraihat et al., 2020; Salloum & al., 2020). This finding is inconsistent with the assumptions of UTAUT2, which emphasize the role of *social influence* in shaping *behavioral intention* prior to actual usage; however, weak normative pressure among late adolescents results in social influence being insufficiently strong to consistently affect users' intrinsic motivation (Abbad, 2021; Chao, 2019). In the context of digital learning, *behavioral intention* is more strongly determined by perceptions of personal benefits such as time efficiency, improved understanding of learning materials, and confidence in one's own abilities (*digital self-efficacy*) rather than by social legitimacy alone, aligning with evidence that technology usage intention is formed only when social influence is reinforced by positive learning experiences and trust in the system (Al-Rahmi & al., 2022; Siron et al., 2020). The absence of this mediating effect underscores that edtech platform development and promotional strategies should integrate social approaches with the strengthening of individual value propositions, such as trial features, simulated learning experiences, and outcome-based reviews, in order to foster more meaningful and sustainable *behavioral intention* (Kohnke & Moorhouse, 2023).

According to UTAUT2, social influence should shape behavioral intention, which then drives actual use. However, this sequential relationship was not observed. One explanation is that social cues do not generate sufficient normative pressure to influence adolescents' internal motivations. Students' engagement appears to be driven more by expected benefits such as comprehension improvement or time efficiency, rather than external endorsement. This aligns with Siron et al. (2020), who found that behavioral intention emerges only when social influence is reinforced by positive experiences or confidence in the technology.

The absence of mediation suggests that social influence, when not supported by personal value perception, digital self-efficacy, or intrinsic motivation, lacks the cognitive weight to shape intention. For developers, this underscores that promotional strategies built only on social proof such as endorsements from friends, teachers, or influencers may fall short. A more effective approach involves combining social strategies with reinforcement of individual value, for instance through outcome-based reviews, trial features, or user experience simulations.

Price Value and Its Influence on User Behavior

The third hypothesis confirmed a significant positive relationship between price value and user behavior ($t = 4.845$; $p = 0.000$), leading to the acceptance of H3. This result represents the strongest statistically significant relationship in the model, highlighting that students' perceptions of price fairness and benefit trade-off are key motivators of active Ruangguru usage. Price value in this context extends beyond subscription cost, encompassing the perceived quality and relevance of the educational content.

The results of the third hypothesis testing indicate that *price value* has a positive and significant effect on user behavior in using the Ruangguru application, confirming that perceptions of price fairness and the balance between cost and benefits are key determinants in encouraging active usage among students (Alqahtani & Rajkhan, 2020; Rahman & al., 2021). This finding reinforces the view that *price value* not only represents the magnitude of subscription fees but also reflects content quality, material relevance, and perceived academic benefits within the context of paid digital learning (Alam et al., 2022; Pham et al., 2021). Among secondary school students with financial constraints, *behavioral intention* and actual usage behavior tend to emerge when edtech platforms are able to demonstrate clear *value for money*, aligning with the cost–benefit evaluation approach in digital education consumer behavior (Ho & al., 2020; Yakubu & Dasuki, 2022). Considering the socioeconomic background of respondents, the majority of whom come from lower- to middle-income families, these results imply that transparent and flexible pricing strategies supported by discount schemes, educational subsidies, or tiered packages are effective approaches to enhance engagement and sustain continued use of Ruangguru.

This finding supports the conceptualization of price value as the trade-off between cost and benefits (Juwairiyah et al., 2022). It is especially relevant for secondary school students who often face financial constraints. (Hameed & Sumari, 2024) similarly emphasize that adoption of paid educational technology hinges on whether the pricing is seen as fair and justifiable. Students are unlikely to sustain usage unless there is a clear value-for-money perception.

The local socioeconomic context also strengthens this conclusion. Many respondents come from lower-middle-income households, where educational spending is carefully considered. Thus, affordable pricing, discounts, and school-supported subsidies strongly influence engagement. Anchoring this discussion in consumer behavior theories, the finding aligns with behavioral cost-benefit models, which argue that learners evaluate perceived academic returns against financial outlay. For Ruangguru, this implies the need for transparent and flexible pricing strategies, including tiered packages, reward systems, or micro-payment schemes that resonate with students' economic realities.

Behavioral Intention Toward User Behavior

The fifth hypothesis revealed that behavioral intention does not significantly affect actual behavior ($t = 0.613$; $p = 0.540$), leading to the rejection of H5. This demonstrates an "intention–behavior gap," where expressed willingness to use Ruangguru does not translate into consistent engagement.

This gap may arise from practical barriers such as time constraints, distractions from social media, or a preference for offline learning. (Sheeran, 2002) highlights that intention predicts behavior only when supported by favorable conditions and strong internal motivation. Within the UTAUT2 framework, behavioral intention is expected to mediate factors such as price value and expectancy, yet its failure in this study suggests the influence of unmeasured variables like self-regulation, digital self-efficacy, and perceived barriers. Adolescents, in particular, may still struggle to convert intentions into autonomous learning habits.

These findings align with (Liu et al., 2025), who found that in mobile learning environments, external factors such as academic pressure, home learning conditions, and intrinsic motivation often outweigh rational intention. For practice, this highlights that strengthening intention alone is insufficient. Developers should also provide tools that convert intention into action, such as reminders, progress trackers, goal-setting features, and reward mechanisms. Involving teachers and parents in reinforcing digital learning behaviors may further help bridge the gap.

CONCLUSION

This study concludes that among high school students in Duren Sawit, East Jakarta, price value is the only factor that significantly influences Ruangguru app usage, while social influence and behavioral intention show no meaningful effect. These findings underscore the existence of an intention behavior gap, suggesting that actual adoption is shaped more by immediate perceived benefits than by planned intentions. Theoretically, this research contributes to refining the UTAUT2 framework in the Indonesian educational context by highlighting the limited role of social influence and intention, and emphasizing the centrality of perceived value in digital learning adoption. Practically, the results stress the importance of Ruangguru's pricing strategy ensuring that pricing remains transparent, flexible, and aligned with the academic value students expect. Developers should focus on value-driven features, such as progress tracking or gamification, to strengthen engagement beyond social endorsement. This study is limited by its cross-sectional design and narrow geographic focus. Future research should incorporate additional factors such as self-efficacy, digital literacy, and learning outcomes, and compare urban versus rural settings to capture broader behavioral variations. Longitudinal and qualitative approaches would also provide deeper insights into how student perceptions and adoption patterns

REFERENCES

Abbad, M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems. *Education and Information Technologies*, *26*. https://doi.org/10.1007/s10639-021-10440-1

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Simintiras, A. C. (2023). Examining the role of intention–behavior gap in mobile learning adoption: Evidence from developing countries. *Computers & Education*, *195*, 104672. https://doi.org/10.1016/j.compedu.2023.104672

Alam, Md. S., Ahmad, N., Naveed, Q. N., Patel, A., Abohashrh, M., & Khaleel, M. A. (2022). E-learning services to achieve sustainable learning outcomes. *Sustainability*, *14*(5). https://doi.org/10.3390/su14052671

Al-Fraihat, D., Joy, M., Sinclair, J., & Masa'deh, R. (2020). Evaluating E-learning systems success. *Computers in Human Behavior*, *102*. https://doi.org/10.1016/j.chb.2019.106272

Alqahtani, M. A., & Rajkhan, A. A. (2020). E-learning critical success factors during COVID-19 pandemic. *Education and Information Technologies*, *25*. https://doi.org/10.1007/s10639-020-10219-y

Al-Rahmi, W. M., & al., et. (2022). Digital learning adoption and student engagement. *Sustainability*, *14*(3). https://doi.org/10.3390/su14031536

Bhikuning, D., Wasiati, H., & Rahmadani, A. N. (2024). Dampak Keputusan Investasi, Kinerja Keuntungan dan Komposisi Modal Terhadap Pencapaian Nilai Entitas Ritel (Sektor Supermarket dan Convenience Store) Yang Terdaftar di BEI Periode 2011-2022. *Jurnal Ilmiah Global Education*, *5*(1), 76–91. https://doi.org/10.55681/jige.v5i1.2101

Bond, M., & al., et. (2021). Emergency remote teaching in higher education: A systematic review. *Educational Technology Research and Development*, *69*. https://doi.org/10.1007/s11423-021-10023-8

Brailas, A., Koskinas, K., & Dafermos, M. (2021). Educational technology adoption and adolescent autonomy. *Education and Information Technologies*, *26*. https://doi.org/10.1007/s10639-021-10485-2

Chao, C.-M. (2019). Factors determining the behavioral intention to use mobile learning. *Interactive Learning Environments*, *27*(1). https://doi.org/10.1080/10494820.2018.1481106

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2020). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *22*(4), 987–1003. https://doi.org/10.1007/s10796-019-09971

Hameed, A., & Sumari, M. (2024). Pricing fairness and adoption of paid educational technology. *Journal of Educational Technology & Online Learning*, *7*(1).

Ho, T.-H., & al., et. (2020). Examining consumers' adoption intention of paid mobile learning services. *Interactive Learning Environments*, *28*(6). https://doi.org/10.1080/10494820.2019.1703016

Ikhsan, K., & Sunaryo, D. (2020). Technology Acceptance Model, Social Influence and Perceived Risk in Using Mobile Applications: Empirical Evidence in Online Transportation in Indonesia. *Jurnal Dinamika Manajemen*, *11*(2), 127–138.

Jainuri, N. & Y. H. (2021). PERANCANGAN DAN PEMBUATAN APLIKASI MOBILE POINT OF SALE PADA OUTLET MAKARONI JUDES BERBASIS ANDROID. *Jurnal IPSIKOM*, *9*(2), 44–52.

Juwairiyah, I., Andrianto, M., & Syafitri, R. (2022). Peran Perempuan dalam Membangun UMKM di Kota Tanjungpinang Article Info. *Jurnal Hukum, Humaniora, Masyaratat, Dan Budaya*, *2*(2), 150–160. https://doi.org/10.33830/humayafhisip

Kohnke, L., & Moorhouse, B. L. (2023). Adopting digital learning tools: Student motivation and intention in post-pandemic education. *Education and Information Technologies*, *28*. https://doi.org/10.1007/s10639-023-11641-4

Lewis, K. L., Howard, S. J., Verenikina, I., & Kervin, L. K. (2023). Parent perspectives on young children's changing digital practices: Insights from Covid-19. *Journal of Early Childhood Research*, *21*(1), 76–90. https://doi.org/10.1177/1476718X221145486

Liu, Y., Zhang, H., & Li, X. (2025). Beyond intention: Understanding barriers to mobile learning adoption among high school students. *Educational Technology Research and Development*, *73*(2), 421–440. https://doi.org/10.1007/s11423-025-10234-1

Martin, F., & Bolliger, D. U. (2022). Engagement matters: Student perceptions on the importance of engagement strategies in online learning. *Online Learning Journal*, *26*(1). https://doi.org/10.24059/olj.v26i1.2595

Nguyen Trong, N., & Nguyen, C. T. (2021). Firm performance: the moderation impact of debt and dividend policies on overinvestment. *Journal of Asian Business and Economic Studies*, *28*(1), 47–63. https://doi.org/10.1108/JABES-12-2019-0128

Nurrisa, F., Hermina, D., & Norlaila. (2025). Pendekatan Kualitatif dalam Penelitian: Strategi, Tahapan, dan Analisis Data. *Jurnal Teknologi Pendidikan Dan Pembelajaran (JTPP)*, *02*(03), 793–800.

Pham, L., Limbu, Y. B., Bui, T. K., Nguyen, H. T., & Pham, H. T. (2021). Does e-learning service quality influence e-learning student satisfaction and loyalty? *Education and Information Technologies*, *26*. https://doi.org/10.1007/s10639-020-10330-y

Rahman, Md. M., & al., et. (2021). Determinants of students' adoption of paid e-learning platforms. *Education and Information Technologies*, *26*. https://doi.org/10.1007/s10639-021-10462-9

Rasheed, R. A., Kamsin, A., & Abdullah, N. A. (2022). Challenges in the online component of blended learning: A systematic review. *Computers & Education*, *181*. https://doi.org/10.1016/j.compedu.2022.104444

Robiul Rochmawati, D., Hatimatunnisani, H., & Veranita, M. (2023). Mengembangkan Strategi Bisnis di Era Transformasi Digital. *Coopetition : Jurnal Ilmiah Manajemen*, *14*(1), 101–108. https://doi.org/10.32670/coopetition.v14i1.3076

Salloum, S. A., & al., et. (2020). Factors affecting the adoption of e-learning systems in higher education. *Education and Information Technologies*, *25*. https://doi.org/10.1007/s10639-020-10157-9

Sheeran, P. (2002). Intention–behavior relations: A conceptual and empirical review. *European Review of Social Psychology*, *12*(1), 1–36. https://doi.org/10.1080/14792772143000003

Siron, Y., Wibowo, A., & Narmaditya, B. S. (2020). Factors affecting the adoption of e-learning in higher education. *Journal of Educational Technology Systems*, *49*(2). https://doi.org/10.1177/0047239520934017

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2020). Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. *Journal of the Association for Information Systems*, *21*(3).

Yakubu, M. N., & Dasuki, S. I. (2022). Assessing the role of perceived value in students' intention to use e-learning systems. *Heliyon*, *8*(1). https://doi.org/10.1016/j.heliyon.2022.e08754

Zacharis, G., & Nikolopoulou, K. (2022). Factors predicting University students' behavioral intention to use eLearning platforms in the post-pandemic normal: an UTAUT2 approach with "Learning Value." *Education and Information Technologies*, *27*, 12065–12082. https://doi.org/10.1007/s10639-022-11116-2