RESEARCH ARTICLE

Autonomous Ride-Hailing Adoption Among Generation Z: The Roles of Innovation Attributes and Peer Imitation in Switching Intentions

Wenjiao Zhang[1] (zhangwj@tsinghua.edu.cn), Peng Xing[1] (xingp@tsinghua.edu.cn)

[1] Department of Computer Science and Technology, Tsinghua University, Beijing, China

Abstract

Autonomous ride-hailing is beginning to move from demonstration projects into limited public service, creating a practical question for ride-hailing users: under what conditions would they switch from a human-driven service to a driverless one? This study examines switching intention among Generation Z consumers. A scenario-based survey was administered to 91 undergraduate students, and the data were analyzed using partial least squares structural equation modeling. Perceived speed advantage, compatibility with respondents' routines, and imitation of peers under uncertainty were all positively associated with switching intention. The model explained 41.3% of the variance in switching intention. Follow-up comparisons by gender and prior ride-hailing frequency did not show statistically significant differences in the estimated paths. The findings suggest that switching to autonomous ride-hailing is shaped not only by perceived service improvements but also by whether the service feels compatible with everyday mobility habits and whether peer use reduces uncertainty.

Keywords — Autonomous vehicles; Ride-hailing; Diffusion of innovation; Herd behavior; Switching intention; Generation Z

1 Introduction

Autonomous vehicles (AVs) have moved from speculative prototypes to limited public ride-hailing services. Waymo, for example, describes its service as fully autonomous ride-hailing available in selected U.S. cities, while public agencies continue to emphasize that automated driving systems remain an evolving vehicle-safety domain [1, 2]. This shift matters for ride-hailing because it introduces a substitute for the familiar human-driven trip rather than an entirely new transportation category. Generation Z (i.e., individuals born roughly between the mid-1990s and early 2010s) is a relevant segment for this transition because its members are accustomed to smartphones, app-based services, and digitally mediated transactions [3, 4].

The transition from conventional ride-hailing to autonomous alternatives is not automatic. Consumers must weigh possible service benefits, such as more predictable availability or shorter waits, against concerns about safety, reliability, and the absence of a human driver [5, 6]. Prior research on AV acceptance has often used broad population samples and private-vehicle scenarios [7, 8]. Less is known about switching from an incumbent ride-hailing service to an autonomous one, especially among younger users who already rely on app-based mobility.

This study addresses two research questions. First, drawing on the diffusion of innovation (DoI) theory [9], we ask whether the perceived speed advantage and compatibility of autonomous ride-hailing services predict Generation Z consumers' intentions to switch away from conventional ride-hailing. Second, grounded in imitation theory [10, 11], we ask whether the tendency to imitate peers who adopt autonomous ride-hailing strengthens switching intention, given the technology's unfamiliarity and associated risks. A supplementary question examines whether demographic subgroups, defined by gender and ride-hailing frequency, exhibit different switching patterns.

By integrating DoI attributes and imitation behavior within a single model, this study makes three contributions. First, it applies innovation diffusion theory to autonomous ride-hailing rather than to private AV ownership. Second, it uses switching intention as the dependent variable, which better fits a setting in which an incumbent service already exists. Third, it reports evidence from a Generation Z sample, a cohort for which mobile, on-demand services are already part of everyday consumption.

2 Related Work

Rogers' diffusion of innovation theory [9, 12] identifies five attributes of an innovation that shape its rate of adoption: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage captures the degree to which an innovation is perceived as superior to the product or practice it replaces. Compatibility reflects the extent to which the innovation aligns with an adopter's existing values, prior experiences, and current needs. Complexity describes the perceived difficulty of understanding and using the innovation. Trialability refers to the possibility of experimenting with the innovation on a limited basis before full commitment, and observability denotes the visibility of the innovation's results to others in the social system.

Across a wide range of technological contexts, including internet banking [13], mobile banking [14], small-business information systems [15], and ride-sharing platforms [16], relative advantage and compatibility have

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consistently emerged as the strongest predictors of adoption and behavioral intention [17–19]. Complexity, trialability, and observability remain important DoI attributes, but they are difficult to measure cleanly when most respondents have no direct experience with the focal service [20]. In the present context, the passenger-facing interface resembles a conventional ride-hailing app; trial use is geographically constrained, and observability depends on whether autonomous services are visible in a respondent's local environment. For these reasons, this study focuses on two attributes that respondents can evaluate after exposure to a common scenario: relative advantage and compatibility.

Switching intention refers to a user's resolve to discontinue an incumbent service and begin using a substitute [21]. Whereas adoption intention presumes a new-to-category entry, switching intention captures a displacement dynamic in which the consumer already uses a comparable service. This distinction matters for autonomous ride-hailing because Generation Z consumers are, by and large, existing users of driver-operated ride-hailing platforms. Their decision is not whether to use ride-hailing for the first time, but whether to shift to an autonomous variant.

Sun [11] introduced the construct of "imitating others" to the technology adoption literature, drawing on classical imitation theory [10, 22]. Imitating others refers to the process by which an individual observes peers' choices and replicates them, not primarily to conform to social expectations but to reduce the risk of making a poor decision under uncertainty. This mechanism differs from the subjective norm construct in the theory of planned behavior [23] and in the unified theory of acceptance and use of technology [24], where the motivation is compliance with perceived social pressure. Imitation, by contrast, represents an informational shortcut: when a technology is unfamiliar and its outcomes uncertain, following the crowd functions as a risk-mitigation heuristic [25].

In technology adoption, imitation can occur when users treat others' adoption choices as information about the usefulness or safety of an unfamiliar system [11, 25, 26]. Autonomous ride-hailing has the same uncertainty profile: the service is novel to many consumers, and safety perceptions remain salient in public evaluations of automated vehicles [5, 6].

Generation Z, variously labeled digital natives, iGen, or the post-millennial cohort, has grown up immersed in smartphones, social media, and on-demand digital services [3, 27]. These formative experiences have produced several behavioral tendencies relevant to the present study. First, Generation Z exhibits a strong preference for speed and immediacy [4]. An autonomous ride-hailing service that reduces wait times by optimizing fleet dispatch through algorithmic routing should therefore hold particular appeal. Second, Generation Z is accustomed to technology-mediated transactions and tends to evaluate new technologies through the lens of lifestyle fit rather than technical specification [3]. Third, members of this cohort are heavily influenced by peer behavior, as demonstrated in studies of e-book adoption [28], mobile commerce [29], and purchasing decisions shaped by social media [30]. These patterns make peer imitation a plausible part of Generation Z's switching calculus for autonomous ride-hailing.

Despite these characteristics, empirical work on Generation Z's response to autonomous mobility remains sparse. Most autonomous vehicle acceptance studies have surveyed broad age ranges and concentrated on private ownership rather than shared-ride services [7, 31, 32]. A few studies have addressed autonomous taxis or shuttles [33, 34], but the specific question of Generation Z's intention to switch from conventional to autonomous ride-hailing remains underdeveloped in the literature.

3 Study

In our study, we analyze the impact of three factors in autonomous ride-hailing: speed advantage, compatibility, and imitation of peers. Relative advantage is the single most consistent predictor of innovation adoption in the DoI literature [12, 17]. The greater the perceived improvement over the incumbent service, the stronger the behavioral intention to switch [18, 19]. For autonomous ride-hailing, a primary source of relative advantage lies in the potential for shorter wait and travel times. In principle, autonomous fleets can be dispatched and repositioned centrally, and riders may perceive them as less dependent on individual driver availability [33]. For passengers, this potential is most visible as a possible reduction in waiting time or a more predictable pickup. On this basis, we hypothesize that the perceived speed advantage of autonomous ride-hailing positively affects switching intention from conventional ride-hailing (H1).

Compatibility with existing lifestyles, habits, and values increases the likelihood that a consumer will adopt an innovation [9, 18]. Prior research on ride-sharing adoption has confirmed that compatibility significantly predicts behavioral intention [16]. For Generation Z, whose daily routines are organized around mobile applications and on-demand services, an autonomous ride-hailing service that mirrors the familiar app-based booking and payment process should be highly compatible. Furthermore, Generation Z's general openness to technology-driven experiences [3] is likely to align with the concept of a fully automated ride. We therefore hypothesize that the perceived compatibility of autonomous ride-hailing positively affects switching intention from conventional ride-hailing (H3).

Furthermore, under conditions of uncertainty, individuals tend to observe the choices of others and replicate them as a means of reducing decision risk [10, 11]. Autonomous ride-hailing remains unfamiliar to most consumers, and publicized safety incidents have sustained perceptions of technological risk [5, 35]. When Generation Z consumers see peers using autonomous ride-hailing—whether through direct observation, social media posts, or word of mouth—they may infer that the service is viable and safe, thereby lowering their own perceived risk. Peer imitation has been shown to operate in technology adoption across multiple domains [25, 26]. We hypothesize that imitating others positively influences the intention to switch from conventional ride-hailing to autonomous ride-hailing. Figure 1 illustrates the research model.

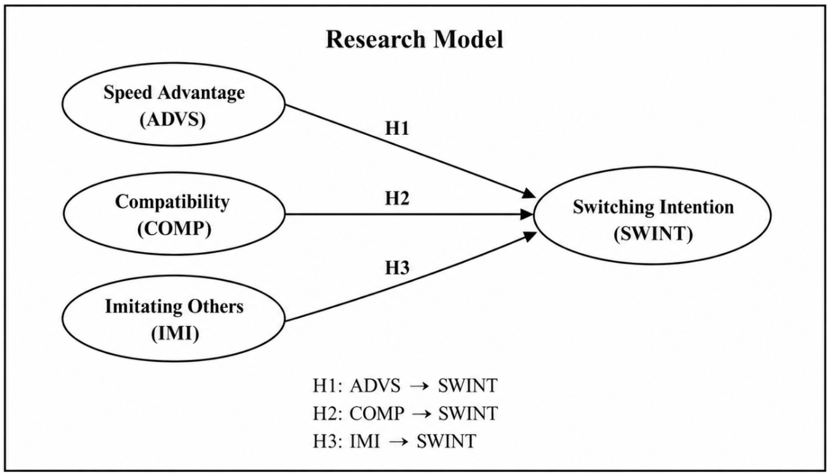

Figure 1: Research model depicting the hypothesized relationships between speed advantage, compatibility, imitating others, and switching intention for autonomous ride-hailing services.

3.1 Materials and Methods

Because autonomous ride-hailing is not yet widely available, we employed a scenario-based survey approach. Respondents first watched a three-minute video demonstrating an autonomous ride-hailing service in operation, including footage of a passenger summoning a vehicle via a mobile application, riding without a human driver, and arriving at the destination. The video was drawn from publicly available promotional material produced by an autonomous vehicle manufacturer. This approach gives respondents a common reference point before they answer intention items, which is important when direct experience with the service is limited [36, 37].

The target population was Generation Z. We collected data from 91 undergraduate students enrolled in business courses at one institution in the United States. Participation was voluntary and offered a small course credit incentive. All participants confirmed that they had used a ride-hailing service at least once within the past twelve months, ensuring baseline familiarity with the incumbent service. The sample size exceeds the minimum threshold for partial least squares structural equation modeling (PLS-SEM), which requires a sample at least ten times the largest number of structural paths directed at a single construct [38]. In our model, the maximum is three paths directed at switching intention, yielding a minimum requirement of 30 observations. Table 1 summarizes the demographic profile of the sample.

All constructs were measured with items adapted from previously validated instruments (see Appendix A). Responses were recorded on a seven-point Likert scale anchored at "strongly disagree" (1) and "strongly agree" (7), except for switching intention, which used three semantic differential items adapted from Bansal et al. [21] (e.g., "Rate the likelihood that you would switch from your current ride-hailing service to an autonomous ride-hailing service: Likely–Unlikely"). Using different response formats does not eliminate common method bias, but it can reduce response-pattern consistency across the questionnaire [39].

Speed advantage items (four items) were drawn from Moore and Benbasat [20] and adapted to the autonomous ride-hailing context. Compatibility items (five items) were similarly adapted from Moore and Benbasat [20] and Al-Jabri and Sohail [14]. Imitating others (four items) was measured using scales from Sun [11]. Reverse-coded items were removed after a pilot study with 45 respondents revealed inconsistent factor loadings, consistent with research documenting the problems that reverse-worded items introduce [40].

Attention-check and speeder-trap items were embedded to identify careless respondents [41–43]. Five responses were excluded on the basis of these checks, yielding a final usable sample of 91. A pretest involving eight graduate students was conducted prior to the pilot study to refine item wording for the autonomous ride-hailing context.

Structural equation modeling with the partial least squares algorithm (PLS-SEM) was employed using SmartPLS 3.0 [38]. PLS-SEM is appropriate for exploratory research with relatively small samples, does not require multivariate normality, and accommodates reflective measurement models [38, 44]. The analysis proceeded in

Table 1: Demographic characteristics of the sample (N = 91).

Characteristic	Category	%
Gender	Female	61.5
	Male	38.5
Smartphone ownership	Yes	100.0
Prior AV exposure	Yes (seen in person or video)	22.0
	No	78.0
Ride-hailing frequency (past 12 months)	Less than once per month	35.2
	1–3 times per month	41.8
	4 or more times per month	23.1
Current neighborhood	Urban	37.4
	Suburban	47.3
	Rural	15.4
Personal vehicle access	Yes	68.1
	No	31.9

Table 2: Construct definitions.

Construct	Definition
Speed Advantage (ADVS)	The perceived improvement in pickup and travel speed offered by autonomous ride-hailing over conventional ride-hailing.
Compatibility (COMP)	The degree to which autonomous ride-hailing is perceived as consistent with the user's lifestyle, values, and existing technology habits.
Imitating Others (IMI)	The tendency to replicate peers' observed decisions to use autonomous ride-hailing as a means of reducing decision uncertainty.
Switching Intention (SWINT)	The user's stated resolve to switch from conventional ride-hailing to autonomous ride-hailing when the service becomes available.

two stages: evaluation of the measurement model (outer model) and evaluation of the structural model (inner model).

4 Results and Discussion

Table 2 presents the construct definitions. Table 3 reports the outer model loadings. All item loadings exceed the 0.70 threshold, indicating acceptable indicator reliability [38].

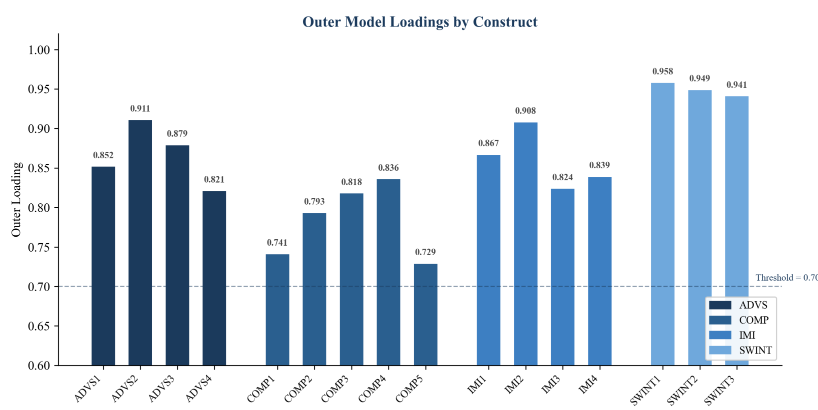

Figure 2: Outer model loadings.

Table 4 provides the descriptive statistics and the Fornell–Larcker criterion values for discriminant validity assessment. Composite reliability (CR) values for all constructs exceed the 0.70 threshold recommended by Nunnally [45], and average variance extracted (AVE) values exceed 0.50 [46, 47]. The square root of each construct's AVE (shown on the diagonal) is larger than its correlation with any other construct, satisfying the Fornell–Larcker criterion for discriminant validity [46].

We additionally assessed discriminant validity using the heterotrait-monotrait (HTMT) ratio of correlations, a method that has been shown to outperform the Fornell–Larcker criterion [48, 49]. Table 5 reports the HTMT values, all of which fall below the conservative threshold of 0.85 [50,51], confirming adequate discriminant validity.

Table 3: Outer model loadings.

Item	ADVS	COMP	IMI	SWINT
ADVS1	0.852			
ADVS2	0.911			
ADVS3	0.879			
ADVS4	0.821			
COMP1		0.741		
COMP2		0.793		
COMP3		0.818		
COMP4		0.836		
COMP5		0.729		
IMI1			0.867	
IMI2			0.908	
IMI3			0.824	
IMI4			0.839	
SWINT1				0.958
SWINT2				0.949
SWINT3				0.941

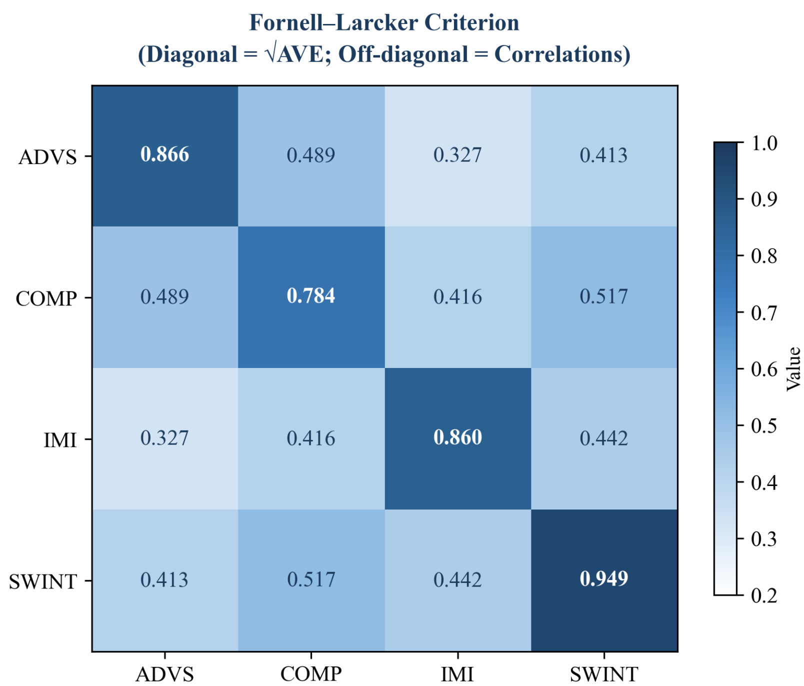

Figure 3: Fornell–Larcker discriminant validity.

Table 4: Descriptive statistics, reliability, and Fornell–Larcker discriminant validity. Diagonal values (bold) are the square root of AVE.

Construct	Items	Mean	SD	CR	ADVS	COMP	IMI
ADVS	4	5.18	1.09	0.924	**0.866**		
COMP	5	4.83	1.37	0.888	0.489	**0.784**	
IMI	4	4.31	1.29	0.920	0.327	0.416	**0.860**
SWINT	3	3.38	1.48	0.966	0.413	0.517	0.442

Note. CR = composite reliability; SD = standard deviation. The SWINT column is omitted from the matrix for space; its $\sqrt{\text{AVE}}$ = 0.949, which exceeds all off-diagonal correlations in its column.

Table 5: Heterotrait-monotrait (HTMT) ratio of correlations.

	ADVS	COMP	IMI	SWINT
ADVS	—			
COMP	0.552	—		
IMI	0.362	0.476	—	
SWINT	0.441	0.574	0.481	—

Table 6: Structural model results: path coefficients, t-values, and hypothesis outcomes.

Hypothesis	Path	β	t-value	p-value	Result
H1	ADVS → SWINT	0.21	2.04	0.043	Supported
H2	COMP → SWINT	0.34	3.19	0.002	Supported
H3	IMI → SWINT	0.24	2.51	0.013	Supported

The standardized root mean square residual (SRMR) for the overall model is 0.087. Because SRMR is a descriptive fit index rather than a decisive test in PLS-SEM, we interpret it alongside the measurement and structural results. Its value is below the commonly reported 0.10 benchmark for approximate fit [51, 52].

Table 6 and Figure 4 present the structural model results, including standardized path coefficients and their significance levels. The overall model explains 41.3% of the variance in switching intention ($R^2 = 0.413$), which indicates moderate explanatory power for a behavioral intention model [38, 44, 53].

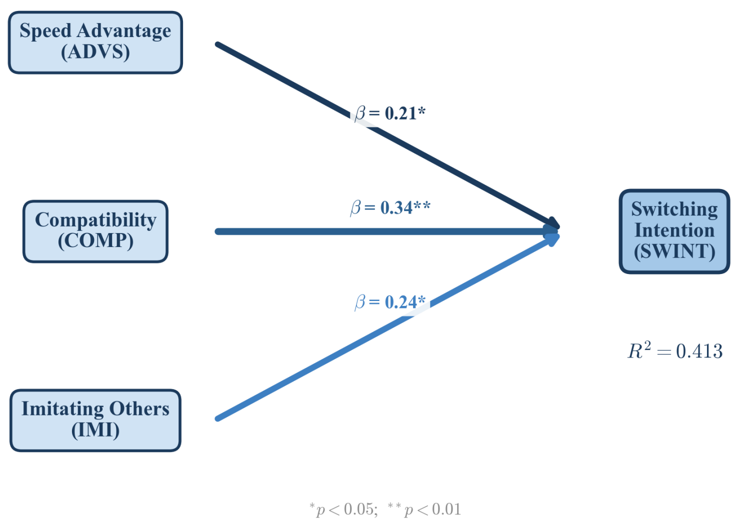

Figure 4: Structural model with standardized path coefficients. All three hypothesized paths are statistically significant.

Testing H1, the speed advantage construct produced a significant positive relationship with switching intention ($\beta = 0.21$, $p = 0.043$). Consumers who perceive autonomous ride-hailing as faster than conventional ride-hailing express greater willingness to switch. This result aligns with prior DoI findings in which relative advantage serves as a primary driver of innovation adoption [12, 17].

H2 is likewise supported: compatibility exhibits the strongest effect on switching intention ($\beta = 0.34$, $p = 0.002$). The strength of this path suggests that Generation Z consumers are particularly attuned to whether autonomous ride-hailing fits their existing digital-first, on-demand lifestyle. This finding is consistent with research on ride-sharing adoption [16] and mobile banking [14], where compatibility consistently ranks among the top predictors.

H3, the imitation-to-switching-intention path, is also significant ($\beta = 0.24$, $p = 0.013$). The result indicates that the tendency to follow peer behavior under conditions of uncertainty meaningfully contributes to switching intention, corroborating Sun's [11] finding that imitation operates as a risk-reduction mechanism in technology adoption. Table 7 consolidates the hypothesis testing outcomes.

As a robustness check, we introduced ride-hailing frequency and personal vehicle access as control variables.

Table 7: Summary of hypothesis outcomes.

Hypothesis	Statement	Supported?
H1	The perceived speed advantage of autonomous ride-hailing positively affects switching intention.	Yes
H2	The perceived compatibility of autonomous ride-hailing positively affects switching intention.	Yes
H3	Imitating others positively affects switching intention from conventional to autonomous ride-hailing.	Yes

Neither was significantly associated with switching intention (ride-hailing frequency: $p = 0.612$; vehicle access: $p = 0.438$), and their inclusion produced a negligible change in R^2 ($\Delta R^2 = 0.005$).

Multigroup comparisons were conducted across gender and ride-hailing usage frequency (low: fewer than three trips per month; high: three or more trips per month). Groups with fewer than ten respondents were excluded to preserve statistical power [38]. No statistically significant differences emerged in path coefficients between male and female respondents or between low-frequency and high-frequency ride-hailing users, suggesting that the model operates consistently across these demographic segments.

5 Conclusion

This study contributes to the innovation diffusion literature in three respects. First, it confirms the applicability of relative advantage (operationalized as speed advantage) and compatibility as predictors of behavioral intention in the autonomous ride-hailing domain. These constructs are well established in contexts such as mobile banking [14] and internet banking [13]. The present results show that they are also useful for explaining stated switching intention in a scenario-based autonomous ride-hailing setting.

Second, by adopting switching intention rather than adoption intention as the dependent variable, this study addresses a theoretical gap. Many DoI studies frame the decision as new-category adoption [54]. The switching framing is useful here because prospective users are already familiar with the service category; the novelty lies in the automation of the driver function, not in app-based ride-hailing itself.

Third, integrating imitation theory with DoI provides a richer account of the decision process than either lens alone. The significant imitation path suggests that, under uncertainty, peer behavior serves as an informational cue that complements the technology's intrinsic attributes. This finding applies the imitation construct validated by Sun [11] to a transportation technology context and supports the view that social learning, beyond direct assessments of service attributes, can shape technology transitions [26].

The results offer several actionable insights for autonomous ride-hailing operators and transportation planners. Generation Z respondents were responsive to the prospect of faster service. Operators should therefore prioritize fleet deployment strategies that minimize wait times and optimize routing, and communicate expected time savings prominently in their mobile applications. When accurate, in-app comparisons between expected wait times for autonomous and conventional ride-hailing could make this advantage more concrete. Compatibility emerged as the strongest predictor. Service providers should design the autonomous ride-hailing experience to resemble the familiar app-based workflow that Generation Z already uses. Integration with familiar payment methods, in-app ride tracking, and clear trip-status information may lower perceived switching costs. Partnerships or campus demonstrations could further help users evaluate whether the service fits their daily routines. The significant imitation effect implies that early adopters can catalyze broader uptake. Operators may benefit from visible, firsthand accounts from early users, such as campus ambassadors or peer demonstration programs. Such programs should present ordinary-use experiences rather than overstated claims, because imitation in this model serves as an informational cue under uncertainty rather than as mere hype. The absence of significant gender- or frequency-based differences suggests that marketing campaigns for Generation Z need not be heavily segmented along these dimensions. A unified value proposition emphasizing speed, lifestyle fit, and credible peer experience may therefore be appropriate for this sample.

Indeed, respondents had not used an autonomous ride-hailing service. The video-based scenario provided a common frame of reference, but simulated exposure cannot fully replicate the experiential qualities of an actual ride. As autonomous services become more widely available, longitudinal research tracking switching behavior before and after direct use would provide stronger causal evidence.

A Measurement Items

Table 8 lists the final measurement items for each construct.

Table 8: Construct measurement items.

Construct	Item	Source
Speed Advantage (7-point Likert)	ADVS1: Autonomous ride-hailing is a faster way to get a ride. ADVS2: Autonomous ride-hailing allows me to reach my destination more quickly. ADVS3: Autonomous ride-hailing is useful in shortening my travel wait time. ADVS4: Autonomous ride-hailing gives me greater control over the speed of my trip.	Al-Jabri et al. [14]; Moore & Benbasat [20]
Compatibility (7-point Likert)	COMP1: Autonomous ride-hailing fits well with how I like to manage my transportation. COMP2: I enjoy trying new technologies. COMP3: Autonomous ride-hailing is compatible with my lifestyle. COMP4: Using autonomous ride-hailing fits into my daily travel routine. COMP5: I would feel comfortable riding in an autonomous vehicle.	Al-Jabri et al. [14]; Moore & Benbasat [20]
Imitating Others (7-point Likert)	IMI1: Autonomous ride-hailing seems to be the future of urban transportation, so I would like to use it too. IMI2: I would follow others in accepting autonomous ride-hailing. IMI3: I would choose autonomous ride-hailing because many other people are using it. IMI4: If I know that many people have already accepted autonomous ride-hailing, I would choose it as well.	Sun [11]
Switching Intention (semantic differential)	SWINT1: Rate the likelihood that you would switch from conventional ride-hailing to autonomous ride-hailing (Likely–Unlikely). SWINT2: Rate the probability that you would switch (Probable–Not Probable). SWINT3: Rate the chance that you would switch (Certain–No Chance).	Bansal et al. [21]

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