

SMART BOARDING HOUSE EXPERIENCE AS A DRIVER OF RESIDENT LOYALTY: THE MEDIATING ROLE OF SATISFACTION

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Abstract

Smart boarding houses combine digital access, intelligent services, residential convenience, and day-to-day management in ways that may shape how residents evaluate where they live. This study investigates whether Smart Boarding House Experience (SBHX), Residential Location Advantage (RLA), Perceived AI Service Integration (PAISI), and Perceived Resident Influence (PRI) are associated with Resident Satisfaction (RS) and Resident Loyalty (RL), and whether Alternative Attractiveness (AA) weakens the satisfaction-loyalty link. Data were collected from 283 adult residents of 18 modern boarding houses in Batam City, Indonesia, between March and June 2026 using purposive sampling and analysed with PLS-SEM. SBHX was modelled as a reflective-formative higher-order construct. SBHX showed the strongest association with satisfaction ($\beta = 0.445$, $f^2 = 0.262$), while satisfaction was the main predictor of loyalty ($\beta = 0.417$, $f^2 = 0.166$). RLA and PAISI were related to loyalty only indirectly through satisfaction, whereas SBHX and PRI retained additional direct associations. AA weakened the satisfaction-loyalty relationship ($\beta = -0.121$, $f^2 = 0.029$). The findings suggest that technology contributes to retention when it improves the wider residential experience, rather than functioning as a stand-alone loyalty mechanism.

Keywords: Artificial intelligence, Smart boarding house, Resident satisfaction, Resident loyalty, PLS-SEM

INTRODUCTION

Smart residential technology is increasingly embedded in everyday housing through connected access, security monitoring, energy management, communication platforms, and intelligent service functions. Yet research has focused predominantly on adoption, examining usefulness, risk, trust, privacy, and behavioural intention (Marikyan et al., 2019; Li et al., 2021; Plohl & Čuš Babič, 2024; Norouzzadeh et al., 2025). These factors explain why people may accept smart-home technologies, but they say less about what happens once those technologies become part of daily living. Evidence on continued use points to satisfaction, usefulness, and habit as important post-adoption considerations (Gu et al., 2019), while recent reviews show that users also evaluate smart homes through functionality, social experience, control, privacy, trust, and ethical concerns (Samancioglu et al., 2024; Yao et al., 2023). The issue is therefore not simply whether residents adopt smart technology, but whether living with it produces an experience that sustains satisfaction and continued preference for the residence.

This question is particularly important in residential settings because technology is persistent rather than episodic. Unlike a hotel chatbot or a retail recommendation system, smart access, surveillance, automated services, and connected utilities remain embedded in residents' everyday routines. Their benefits may accumulate through convenience and personalisation, but so may concerns about data collection, surveillance, autonomy, and provider control. Privacy, reliability, trust, and perceived control are therefore part of the residential experience itself (Schomakers et al., 2021; Chan-Olmsted et al., 2024). Reviews of connected-home technologies likewise identify security, unauthorised access, and data-governance risks (Pattnaik et al., 2023; Buil-Gil et al., 2023). These trade-offs become more pronounced when AI is involved because personalisation often depends on data capture, classification, and continuous processing (Puntoni et al., 2021; Zhang et al., 2023a).

Rental and co-living environments add another layer to this problem. Residents evaluate technology together with location, comfort, safety, privacy, social living, and management responsiveness. Smart technologies can improve service flexibility while also reshaping residents' relationship with housing providers (Ehrenberg & Keinonen, 2021). Research on lived smart-home use shows that technologies must be learned and incorporated into everyday routines rather than simply accepted once (Hargreaves et al., 2018). This supports a socio-technical view of smart housing in which technology interacts with physical conditions, household practices, and resident control

(Sovacool & Furszyfer Del Rio, 2020; Yao et al., 2023). In Indonesia, however, available evidence still concentrates largely on willingness to adopt smart-home technology (Nugroho & Salehudin, 2024). Modern boarding houses therefore provide a useful setting for examining what happens after adoption.

Three related issues remain unresolved. First, adoption research explains initial acceptance but provides limited evidence on whether accumulated smart-living experience leads to satisfaction with the residence and loyalty toward the provider. Satisfaction is central to post-adoption continuance (Bhattacharjee, 2001), yet smart-home continuance research remains less developed than adoption research (Gu et al., 2019). Second, findings from hospitality and retail AI cannot be transferred uncritically to residential settings because living with technology is more persistent, intimate, and data-intensive than short service encounters. Third, technological experience, location advantage, resident influence, and competitive alternatives are often examined separately, even though residents consider them jointly when deciding whether to remain in a property.

This study addresses these issues by examining post-adoption smart boarding-house living among residents in Batam City, Riau Islands, Indonesia. The model considers four resident-perceived attributes: Smart Boarding House Experience (SBHX), Residential Location Advantage (RLA), Perceived AI Service Integration (PAISI), and Perceived Resident Influence (PRI). Resident Satisfaction (RS) represents residents' overall evaluation of their living experience, while Resident Loyalty (RL) captures intentions to stay, choose the residence again, and recommend it. Alternative Attractiveness (AA) is included because satisfaction may not translate into loyalty when competing accommodation is perceived as more appealing.

The study contributes by clarifying how different sources of residential value operate after adoption. SBHX is modelled as a reflective-formative higher-order construct combining smart technology interaction, comfort, social living, safety, and data privacy. PAISI is treated separately to distinguish the broader experience of living in a smart residence from the perceived integration of AI into residential services. The model also examines whether satisfaction links these residential resources to loyalty and whether Alternative Attractiveness weakens that relationship. In this way, smart boarding-house loyalty is treated as an outcome of a socio-technical residential environment rather than as a simple consequence of technological sophistication.

LITERATURE REVIEW

Stimulus-Organism-Response perspective

The Stimulus-Organism-Response (S-O-R) framework provides a useful basis for explaining how residents respond to technology-enabled living environments because it connects environmental cues with internal evaluations and subsequent behaviour (Mehrabian & Russell, 1974). In this study, Smart Boarding House Experience (SBHX), Residential Location Advantage (RLA), Perceived AI Service Integration (PAISI), and Perceived Resident Influence (PRI) represent resident-perceived proximal stimuli arising from technological, spatial, and managerial aspects of the residence. Resident Satisfaction (RS) captures residents' overall cognitive-affective evaluation of their living experience, whereas Resident Loyalty (RL) reflects intentions to remain, choose the residence again, and recommend it. The model also retains direct paths from the four stimuli to loyalty because not all residential value needs to operate through satisfaction. Familiarity with the living environment, difficulty replacing a favourable location, distinctive intelligent services, and psychological attachment may independently encourage residents to stay. Alternative Attractiveness (AA) is introduced as a competitive condition that may limit the extent to which satisfaction is associated with loyalty.

Smart Boarding House Experience and Resident Satisfaction

SBHX refers to the quality residents perceive across the technological, physical, social, safety, and privacy dimensions of a technology-enabled boarding house. It is specified as a reflective-formative higher-order construct comprising Smart Technology Interaction Experience, Residential Comfort Experience, Social Living Experience, Residential Safety Experience, and Data Privacy Experience. Treating these dimensions as interchangeable would overlook an important feature of smart residential living: a property can offer convenient technology while performing poorly on privacy, safety, or social experience. SBHX therefore captures a broader socio-technical experience rather than technology use alone. This interpretation is consistent with research showing that lived smart-home experiences emerge from the interaction of technology with routines, control, safety, privacy, and residents' needs (Hargreaves et al., 2018; Sovacool & Furszyfer Del Rio, 2020; Schomakers et al., 2021; Yao et al., 2023; Samancioglu et al., 2024). A more favourable experience across these dimensions should consequently be associated with greater satisfaction with the residence.

H1: Smart Boarding House Experience has a positive effect on Resident Satisfaction.

Residential Location Advantage and Resident Satisfaction

RLA captures the practical value residents derive from proximity to workplaces or universities, transport, retail, food, healthcare, and other services used in everyday life. Smart technology may alter how residential services are delivered, but it does not eliminate the time and convenience advantages associated with location. A technologically sophisticated property may still be evaluated poorly when daily travel is costly or essential amenities are difficult to reach. Consistent with this argument, residential research identifies accessibility, infrastructure, amenities, and proximity to essential services as recurring sources of location satisfaction (Sahu & Agrawal, 2025). Residents who experience greater locational convenience should therefore evaluate their residence more favourably.

H2: Residential Location Advantage has a positive effect on Resident Satisfaction.

Perceived AI Service Integration and Resident Satisfaction

PAISI concerns residents' perception that genuinely intelligent capabilities are embedded meaningfully in residential services. It is deliberately separated from Smart Technology Interaction Experience: STI concerns whether digital technologies are usable, reliable, and responsive, whereas PAISI concerns whether services display adaptive, predictive, personalised, or conversational intelligence. Functions such as AI service assistants, predictive maintenance, anomaly detection, intelligent energy management, and adaptive recommendations fit this definition; ordinary Wi-Fi, CCTV, QR payment, or electronic locks do not constitute AI merely because they are digital. Studies of AI-enabled services suggest that intelligent functionality can improve convenience, personalisation, efficiency, and satisfaction when users experience it as useful within the service process (Ameen et al., 2021; Prentice et al., 2020; Chotisarn & Phuthong, 2025). Technical sophistication alone, however, is insufficient because AI-related value depends on how users experience interaction, delegation, and data use (Puntoni et al., 2021). Meaningful integration of intelligent services should therefore contribute positively to residents' overall evaluation of the property.

H3: Perceived AI Service Integration has a positive effect on Resident Satisfaction.

Perceived Resident Influence and Resident Satisfaction

PRI captures the extent to which residents believe their preferences, feedback, and choices can influence residential services or aspects of the living environment. This matters in smart housing because greater automation does not necessarily give residents greater control. A human-centred residential system should allow occupants to influence service improvements, technology settings, shared arrangements, or other decisions that affect daily living. Evidence from smart buildings links perceived control with higher occupant satisfaction (Loengbudnark et al., 2023), while research on housing participation and value co-creation similarly shows that involvement can strengthen satisfaction and experiential value (Fakere et al., 2017; Jin et al., 2018; Yi & Gong, 2013; Chen & Wang, 2016). Residents are therefore more likely to be satisfied when they perceive management as responsive and their input as consequential rather than symbolic.

H4: Perceived Resident Influence has a positive effect on Resident Satisfaction.

Resident Satisfaction and Resident Loyalty

RS represents residents' overall cognitive and affective judgement of whether the boarding-house experience meets their expectations and residential needs. RL, by contrast, concerns intended continuance or renewal, willingness to choose the residence again, and recommendation. The distinction matters because a favourable evaluation does not itself constitute loyalty, although it can make continued residence more likely. Satisfaction has long been identified as a key precursor of loyalty and post-adoption continuance (Oliver, 1999; Bhattacharjee, 2001). Comparable patterns have been reported for continued use of smart-home services and smart locks (Gu et al., 2019; Liu et al., 2024), while AI-enabled service studies similarly show that satisfaction can connect technology-related value with loyalty (Prentice et al., 2020; Chotisarn & Phuthong, 2025). Residents who are more satisfied with their living experience should therefore be more inclined to maintain their relationship with the property.

H5: Resident Satisfaction has a positive effect on Resident Loyalty.

Direct routes to Resident Loyalty

Satisfaction need not account for the entire relationship between residential resources and loyalty. SBHX may create experiential embeddedness because replacing a familiar combination of smart interaction, comfort, safety, privacy, and daily routines requires additional learning and adaptation (Burnham et al., 2003). RLA can create a different form of retention value: leaving a well-located property may increase travel time, reduce access to amenities, or disrupt established routines, making an otherwise comparable alternative less attractive (Jones et al., 2000; Burnham et al., 2003). PAISI may differentiate a property when intelligent services are useful, familiar, and difficult to obtain elsewhere, a mechanism consistent with evidence linking AI-enabled service quality with loyalty outcomes (Prentice et al., 2020; Chotisarn & Phuthong, 2025). PRI operates through another route, because residents who can influence their living environment may develop stronger agency and psychological attachment; such

SMART BOARDING HOUSE EXPERIENCE AS A DRIVER OF RESIDENT LOYALTY: THE MEDIATING ROLE OF SATISFACTION

Agus Tamrin Reni

ownership-like feelings have been associated with loyalty in hospitality settings (Pino et al., 2022; Yoon et al., 2025). These distinct mechanisms justify examining direct relationships with loyalty alongside the satisfaction-mediated paths.

H6: Smart Boarding House Experience has a positive effect on Resident Loyalty.

H7: Residential Location Advantage has a positive effect on Resident Loyalty.

H8: Perceived AI Service Integration has a positive effect on Resident Loyalty.

H9: Perceived Resident Influence has a positive effect on Resident Loyalty.

Resident Satisfaction as an evaluative mechanism

The indirect paths address whether residential resources are associated with loyalty partly through residents' overall evaluation of the property. The mechanisms are not identical: SBHX concerns the quality of the integrated living experience, RLA provides spatial utility, PAISI represents intelligent service capability, and PRI reflects resident agency. Each can contribute to satisfaction for different reasons, while greater satisfaction is expected to be associated with stronger loyalty. Estimating the corresponding direct paths at the same time also makes it possible to distinguish indirect-only from complementary or competitive mediation through bootstrapped specific indirect effects rather than relying solely on variance-accounted-for ratios. Given the cross-sectional design, these indirect effects are interpreted as patterns consistent with mediation rather than definitive evidence of temporal causality.

H10: Resident Satisfaction mediates the positive relationship between Smart Boarding House Experience and Resident Loyalty.

H11: Resident Satisfaction mediates the positive relationship between Residential Location Advantage and Resident Loyalty.

H12: Resident Satisfaction mediates the positive relationship between Perceived AI Service Integration and Resident Loyalty.

H13: Resident Satisfaction mediates the positive relationship between Perceived Resident Influence and Resident Loyalty.

Alternative Attractiveness as a boundary condition

AA captures how appealing residents perceive competing accommodation to be in terms of price, location, facilities, technology, services, and overall living conditions. It differs from loyalty because it concerns the external choice set rather than attachment to the current property. Existing evidence does not show a uniform moderating effect: Kim et al. (2018) found no moderation of the satisfaction-loyalty relationship in mobile communication services, whereas Zhang et al. (2023b) reported a weakening effect in mobile payments. Residential decisions may make alternative attractiveness more consequential because changing accommodation involves not only service comparison but also rent, commuting, neighbourhood access, moving effort, and disruption to daily routines. Satisfaction should therefore translate less strongly into loyalty when residents perceive competing boarding houses as offering substantially more attractive alternatives.

H14: Alternative Attractiveness negatively moderates the positive relationship between Resident Satisfaction and Resident Loyalty, such that the relationship is weaker when Alternative Attractiveness is high.

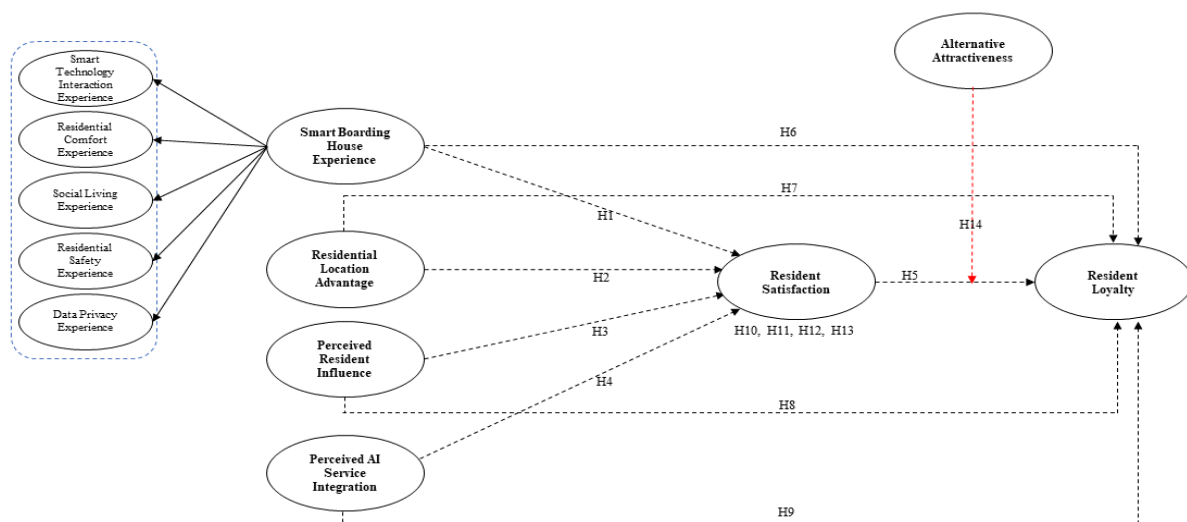


Figure 1. Proposed conceptual framework

METHOD

Research design and respondents

Between March and June 2026, data were collected from adult residents of modern boarding houses in Batam City, Riau Islands, Indonesia, using a cross-sectional survey, with the individual resident as the unit of analysis. Purposive sampling was appropriate because participation depended on prior residential and technology-use experience. Respondents were recruited from 18 boarding houses through property managers and QR codes displayed at participating properties. A modern boarding house was defined as rental accommodation that combines digitally enabled resident services with connected, automated, or intelligent residential functions. To participate, residents had to be at least 18 years old, have lived in the property for a minimum of three months, and have used at least one smart or digital residential service. These criteria were intended to capture evaluations based on actual post-adoption experience rather than hypothetical views of residential technology. Of the 340 residents who accessed the questionnaire, 306 submitted responses and 283 met the eligibility and data-quality requirements, equivalent to 83.2% of questionnaire accesses. The retained sample included both students and working adults who had lived in their properties for periods ranging from three months to more than one year. Their reported technology exposure included smart access, conversational service assistance, anomaly or intrusion alerts, predictive-maintenance notifications, and intelligent energy management (Table 1).

Data screening and response quality

Screening of the final 283×46 data matrix identified no missing values, duplicate response profiles, or complete straight-lining. Six respondents produced strings of ten or more identical answers, but none used the same response throughout the questionnaire. Because the instrument was organised into construct-specific blocks, such response runs were not treated by themselves as sufficient evidence of careless responding. The six cases also satisfied the remaining eligibility and data-quality criteria and were therefore retained.

Measurement and model specification

The questionnaire contained 46 indicators rated on a seven-point scale from 1 (strongly disagree) to 7 (strongly agree). SBHX was specified as a reflective-formative Type II higher-order construct comprising five reflective dimensions, each measured with four items: Smart Technology Interaction Experience (STI), Residential Comfort Experience (RCE), Social Living Experience (SLE), Residential Safety Experience (RSE), and Data Privacy Experience (DPE). RLA, PRI, RS, and AA were each measured with four items, whereas PAISI and RL contained five items each. At the item level, all measures were reflective; at the higher-order level, the five non-interchangeable SBHX dimensions jointly formed the broader residential experience and were estimated using a two-stage procedure (Sarstedt et al., 2019). PAISI was separated from STI by restricting it to adaptive, predictive, personalised, or conversational intelligence rather than general digital usability, while RL focused on continuance or renewal, re-selection, and recommendation to avoid conceptual overlap with AA. Measurement development drew on established work on smart-home experience and privacy, residential location, AI-enabled services, occupant control and participation, satisfaction, loyalty, and switching alternatives (Schomakers et al., 2021; Zhang et al., 2023a; Ameen et al., 2021; Loengbudnark et al., 2023; Chotisarn & Phuthong, 2025; Sahu & Agrawal, 2025; Oliver, 1999; Jones et al., 2000; Zhang et al., 2023b). Item wording was adapted to everyday boarding-house services without altering the intended construct domains. Participation was voluntary, no personally identifying information was requested, and respondents were informed that the data would be used for academic purposes and reported only in aggregate form.

Data analysis

Given the reflective-formative higher-order specification and the need to estimate direct, indirect, and interaction effects within the same model, the data were analysed using PLS-SEM (Hair et al., 2022; Sarstedt et al., 2019). The path-weighting scheme was applied, with Mode A used for reflective constructs and Mode B for the formative higher-order construct; SBHX and the $RS \times AA$ interaction were estimated using two-stage procedures. Structural-path significance was evaluated with 5,000 bootstrap subsamples, two-tailed tests, and percentile confidence intervals, whereas 2,000 bootstrap subsamples were used for the lower-order measurement model. Predictive performance was examined with PLSpredict using ten folds and one repetition. Because this procedure relied on a single random partition, the resulting prediction statistics were treated as indicative evidence of out-of-sample performance rather than as a definitive assessment of predictive capability (Shmueli et al., 2019).

Measurement assessment

Reflective measures were assessed through outer loadings, Cronbach's alpha, ρ_A , composite reliability, average variance extracted (AVE), HTMT, and the Fornell-Larcker criterion, with HTMT serving as the primary check of discriminant validity (Henseler et al., 2015). For the formative SBHX specification, assessment focused on

outer weights and their significance, absolute-contribution loadings, and VIF. The structural model was evaluated using inner VIF, path coefficients and 95% confidence intervals, R^2 , f^2 , specific indirect effects, the $RS \times AA$ interaction, simple slopes, SRMR, and PLSpredict (Hair et al., 2022; Shmueli et al., 2019); f^2 values of approximately 0.02, 0.15, and 0.35 were interpreted as small, medium, and large effects, respectively. Common-method concerns were examined using Harman's single-factor test and full-collinearity VIF. The first unrotated factor accounted for 29.34% of the total variance, while full-collinearity VIF values ranged from 1.16 to 2.46. Neither diagnostic suggested severe common-method contamination, although they cannot exclude common-method variance entirely in a single-source, self-reported design.

RESULTS AND DISCUSSION

Results

The final sample included 283 residents and was predominantly young, with 62.2% aged 18 to 24 years; women accounted for 53.7% and students for 55.8% of respondents. Three quarters had lived in their boarding house for at least seven months, while the most common rent category was IDR 1,000,000 to 1,500,000 per month (42.8%). Exposure to residential technology varied considerably. App-based or biometric access was reported by 81.6% of respondents, compared with 58.0% for conversational service assistance, 42.0% for anomaly or intrusion alerts, 30.7% for predictive-maintenance notifications, and 27.6% for intelligent energy management (Table 1). The measurement results in Table 2 supported the quality of the reflective measures: all 46 indicators were retained, loadings ranged from 0.775 to 0.895 (all $p < 0.001$), reliability coefficients ranged from 0.845 to 0.929, and AVE values from 0.682 to 0.766. The maximum HTMT value was 0.652, and the Fornell-Larcker criterion was also satisfied. Within the formative SBHX specification, four dimensions had significant relative weights. SLE had a non-significant weight ($w = 0.085$, $p = 0.319$), but its significant absolute loading ($\lambda = 0.618$, $p < 0.001$) supported its retention. Formative VIF values of 1.456 to 1.607 indicated no problematic collinearity.

The structural results are reported in Table 3. Inner VIF values ranged from 1.021 to 2.113, while the model accounted for 52.4% of the variance in RS (adjusted $R^2 = 0.517$) and 50.4% in RL (adjusted $R^2 = 0.492$). SBHX showed the largest association with satisfaction ($\beta = 0.445$, $f^2 = 0.262$), followed by PRI ($\beta = 0.228$), PAISI ($\beta = 0.145$), and RLA ($\beta = 0.123$); RS, in turn, was positively associated with RL ($\beta = 0.417$, $f^2 = 0.166$). H1 to H6 and H9 were supported, whereas the direct $RLA \rightarrow RL$ and $PAISI \rightarrow RL$ paths (H7 and H8) were not. The mediation results provide a more differentiated pattern: SBHX and PRI retained significant direct associations with loyalty while also showing significant indirect effects through RS, consistent with complementary mediation, whereas RLA and PAISI were associated with loyalty only through RS. AA also mattered beyond this mediation structure. Its main association with RL was negative ($\beta = -0.340$, $p < 0.001$, $f^2 = 0.223$), and the $RS \times AA$ interaction was negative and significant ($\beta = -0.121$, $p = 0.011$, $f^2 = 0.029$). The estimated RS-RL slope declined from 0.538 at low AA to 0.417 at the mean and 0.296 at high AA, supporting H14. All $Q^2_{predict}$ values were positive and PLS prediction errors were below the linear-model benchmark for every RS and RL indicator. Because PLSpredict was based on a single repetition, these results are treated as favourable predictive diagnostics rather than firm evidence of strong out-of-sample predictive performance. SRMR was 0.044.

Table 1. Respondent profile

Characteristic	Category	Frequency	%
Gender	Male	131	46.3
	Female	152	53.7
Age	18-24	176	62.2
	25-34	84	29.7
	35 and above	23	8.1
	3-6 months	71	25.1
Length of residence	7-12 months	118	41.7
	More than 12 months	94	33.2
	Student	158	55.8
Main occupation	Employee	102	36.0
	Other	23	8.1
	Below IDR 1,000,000	96	33.9
Monthly rent	IDR 1,000,000-1,500,000	121	42.8
	Above IDR 1,500,000	66	23.3
Technology-enabled service used*	App-based or biometric smart access	231	81.6

SMART BOARDING HOUSE EXPERIENCE AS A DRIVER OF RESIDENT LOYALTY: THE MEDIATING ROLE OF SATISFACTION

Agus Tamrin Reni

Conversational service assistant	164	58.0
Anomaly or intrusion detection alerts	119	42.0
Predictive-maintenance notification	87	30.7
Intelligent energy management	78	27.6

Note. Technology-enabled services were multiple-response items; percentages therefore do not sum to 100%.

Table 2. Measurement model and higher-order assessment

Construct	Loading range	Alpha	rho A	CR	AVE	HOC weight / VIF
STI	0.824-0.865	0.873	0.877	0.913	0.724	w = 0.210; VIF = 1.607
RCE	0.794-0.850	0.845	0.851	0.895	0.682	w = 0.416; VIF = 1.531
SLE	0.819-0.890	0.868	0.880	0.910	0.716	w = 0.085; VIF = 1.494
RSE	0.792-0.886	0.865	0.869	0.908	0.713	w = 0.357; VIF = 1.479
DPE	0.783-0.880	0.853	0.859	0.901	0.695	w = 0.255; VIF = 1.456
RLA	0.817-0.879	0.876	0.887	0.915	0.728	-
PAISI	0.775-0.890	0.891	0.900	0.920	0.697	-
PRI	0.836-0.868	0.873	0.874	0.913	0.724	-
RS	0.866-0.895	0.898	0.899	0.929	0.766	-
RL	0.812-0.865	0.898	0.901	0.925	0.711	-
AA	0.834-0.881	0.875	0.896	0.913	0.725	-

Note. Alpha = Cronbach's alpha; rho A = Dijkstra-Henseler's reliability coefficient; CR = composite reliability; AVE = average variance extracted; HOC = higher-order construct; VIF = variance inflation factor.

Table 3. Structural, mediation, and moderation results

Hyp.	Path	Type	β	f^2	p	95% CI	Decision
H1	SBHX → RS	Direct	0.445	0.262	<0.001	[0.355, 0.544]	Supported
H2	RLA → RS	Direct	0.123	0.029	0.004	[0.037, 0.204]	Supported
H3	PAISI → RS	Direct	0.145	0.032	0.001	[0.057, 0.233]	Supported
H4	PRI → RS	Direct	0.228	0.081	<0.001	[0.132, 0.320]	Supported
H5	RS → RL	Direct	0.417	0.166	<0.001	[0.302, 0.523]	Supported
H6	SBHX → RL	Direct	0.150	0.022	0.016	[0.036, 0.277]	Supported
H7	RLA → RL	Direct	0.040	0.003	0.391	[-0.050, 0.131]	Not supported
H8	PAISI → RL	Direct	0.041	0.002	0.411	[-0.056, 0.136]	Not supported
H9	PRI → RL	Direct	0.128	0.023	0.009	[0.031, 0.224]	Supported
H10	SBHX → RS → RL	Indirect	0.186	-	<0.001	[0.128, 0.250]	Supported
H11	RLA → RS → RL	Indirect	0.051	-	0.006	[0.015, 0.088]	Supported
H12	PAISI → RS → RL	Indirect	0.061	-	0.003	[0.023, 0.102]	Supported
H13	PRI → RS → RL	Indirect	0.095	-	<0.001	[0.050, 0.147]	Supported
H14	RS × AA → RL	Moderation	-0.121	0.029	0.011	[-0.210, -0.027]	Supported

Note. β = standardised path coefficient; f^2 = effect size; CI = bootstrap confidence interval. The constitutive main effect of AA on RL was $\beta = -0.340$, $p < 0.001$, $f^2 = 0.223$; it was estimated as part of the moderation model but was not specified as a separate hypothesis.

Discussion

The strongest result in this study is not the effect of AI integration, but the importance of the residential experience as a whole. SBHX showed a markedly larger association with satisfaction than either PAISI or RLA, indicating that residents do not appear to judge a smart boarding house primarily by how advanced its technology is. What matters more is how technology fits with comfort, safety, privacy, social living, and everyday interaction with the residence. This result shifts the emphasis from technological capability to lived residential quality. It accords with evidence that smart-home technologies acquire meaning through their incorporation into everyday routines (Hargreaves et al., 2018) and that privacy and security are experienced as practical features of connected living rather than abstract technical risks (Pattnaik et al., 2023; Buil-Gil et al., 2023). It also supports human-centred accounts in which smart housing is understood as a socio-technical environment rather than a collection of devices (Yao et al., 2023; Samancioglu et al., 2024). The formative results sharpen this point. Comfort and safety supplied more unique information to SBHX, whereas social living contributed less uniquely once the other dimensions were considered, although its significant absolute loading supports its continued inclusion. The evidence therefore favours an integrated conception of smart-residential value over a technology-centred one.

The pattern leading to loyalty was more differentiated. SBHX and PRI remained associated with loyalty after satisfaction was included, while also showing significant indirect associations through satisfaction. For SBHX, this pattern is consistent with experiential embeddedness: residents may become accustomed to a particular combination of technology, comfort, safety, privacy, and daily routines, making the current residence valuable beyond their overall satisfaction with it. PRI appears to operate differently. Residents who believe that their feedback and preferences have consequences may evaluate the residence more favourably while also developing a stronger sense of agency and attachment. This interpretation is compatible with studies linking control and participation to satisfaction (Fakere et al., 2017; Loengbudnark et al., 2023; Chen & Wang, 2016) and psychological ownership to loyalty (Pino et al., 2022; Yoon et al., 2025). RLA and PAISI, however, did not retain direct associations with loyalty. Their significant indirect effects through RS suggest that location and intelligent services matter for retention when residents incorporate those benefits into their overall evaluation of the residence. The PAISI result is especially relevant. Intelligent features were not associated with greater loyalty simply because they were available. Their value appears to depend on whether residents perceive them as improving the broader living experience. This qualification is consistent with post-adoption continuance research (Bhattacharjee, 2001; Gu et al., 2019; Liu et al., 2024) and with AI-service studies in which satisfaction channels technology-related value into loyalty (Prentice et al., 2020; Chotisarn & Phuthong, 2025).

The role of Alternative Attractiveness also shows why satisfaction alone provides an incomplete account of residential loyalty. The negative $RS \times AA$ interaction indicates that the association between satisfaction and loyalty weakened as competing boarding houses became more attractive. The estimated slope fell from 0.538 at low AA to 0.296 at high AA, so the moderating effect, although small in effect-size terms, was substantively interpretable. This result resembles Zhang et al. (2023b), but differs from Kim et al. (2018), who found no corresponding moderation in mobile communication services. One plausible reason lies in the nature of residential choice. Switching accommodation involves rent, commuting, neighbourhood access, facilities, moving effort, and disruption to established routines, rather than a simple change of service provider. The sizeable negative main association between AA and loyalty ($f^2 = 0.223$) reinforces this argument. Competing properties mattered not only because they altered the strength of the satisfaction-loyalty relationship, but also because residents who perceived better alternatives were less inclined to remain. Satisfaction, in other words, is an important source of loyalty but not a shield against an attractive local housing market.

These findings also sharpen the theoretical role of S-O-R in a smart-residential setting. The results do not support a simple sequence in which every favourable stimulus works through the same internal evaluation before producing the same behavioural response. Instead, the mechanisms varied across residential resources. RLA and PAISI were satisfaction-dependent in their associations with loyalty, whereas SBHX and PRI retained additional direct routes. Resident influence is therefore more than a secondary participation variable: it appears to be part of the value structure of human-centred smart living. Likewise, the contrast between SBHX and PAISI suggests that AI sophistication should not be treated as a proxy for smart-residential quality. From a managerial perspective, this distinction matters. Adding intelligent functions is unlikely to strengthen retention if those functions do little to improve comfort, safety, privacy, responsiveness, or residents' control over their living environment. Investment decisions should therefore start with residential problems rather than technology availability. Operators may also benefit from formal mechanisms through which residents can influence service adjustments, while competitive monitoring should extend beyond rent to the mix of location, facilities, technology, and living conditions offered by nearby alternatives.

These interpretations should be read within the study's design constraints. The cross-sectional and self-reported data do not establish temporal causality, and the common-method diagnostics, although not indicating severe contamination, cannot eliminate that possibility. Longitudinal work could establish whether changes in smart-residential experience precede changes in satisfaction and actual lease renewal. Generalisability is also limited by the single-city setting and the predominance of younger respondents. Although residents were drawn from 18 boarding houses, property identifiers were not retained in the analytical dataset, preventing assessment of within-property dependence; future studies should preserve these identifiers and examine clustering when residents share management, location, and technology infrastructure. AI exposure also varied substantially across respondents, which argues for clearer empirical separation of conventional digital services, connected automation, and genuinely adaptive or predictive AI. Methodologically, future instrument development should include a global criterion measure for redundancy assessment of the formative SBHX construct, while repeated PLSpredict partitions and formal predictive comparisons would provide more stable evidence of predictive performance. Extending the model

to affordability, lease conditions, social ties, service recovery, and local housing supply would also help determine whether the patterns observed here persist when broader residential constraints are considered.

CONCLUSION

Post-adoption loyalty in modern smart boarding houses is not explained by technological sophistication alone. Residents were more satisfied when smart technology formed part of a broader residential experience that also encompassed comfort, safety, privacy, social interaction, location, and opportunities to influence the living environment. SBHX and PRI were associated with loyalty both directly and through satisfaction, whereas the contributions of RLA and PAISI to loyalty were evident only through satisfaction. This distinction is important: favourable location and intelligent services appear to support retention when residents experience them as improving the residence as a whole, rather than simply because those features are available. The weakening effect of Alternative Attractiveness further shows that satisfaction does not guarantee loyalty when competing accommodation is perceived as more appealing. The study therefore positions smart residential innovation as a human-centred, socio-technical proposition in which technology creates retention value through its integration with everyday living conditions, resident agency, and the competitive residential environment.

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SMART BOARDING HOUSE EXPERIENCE AS A DRIVER OF RESIDENT LOYALTY: THE MEDIATING ROLE OF SATISFACTION

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