https://doi.org/10.7896/j.3349 Studies in Agricultural Economics 128 (2026) 45-58

Scientific Article

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Technology adoption for sustainable agriculture in a transition country: An UTAUT analysis of the Albanian horticulture sector

ABSTRACT

This study examines how farmers form intentions to adopt sustainability-oriented technologies, such as biological control and precision tools, in Albanian horticulture, a transitional smallholder context characterised by fragmented structures and weak advisory support. Using original survey data from 206 apple and greenhouse-vegetable producers, the analysis applies the Unified Theory of Acceptance and Use of Technology (UTAUT), with construct validation via exploratory factor analysis and estimation through multiple regression including demographic moderators. Results indicate that effort expectancy and social influence are the main drivers of behavioural intention, whereas performance expectancy, although positively perceived, does not exert an independent effect once feasibility and social endorsement are considered. No significant moderation by age, education, or farming experience is detected, and the model explains nearly half of the variance in intention. The findings refine UTAUT's application to transitional agricultural systems by highlighting a feasibility- and trust-based pathway in intention formation and suggest that adoption policies should prioritise reducing learning frictions through sequenced onboarding, short demonstration cycles, and endorsement by trusted agronomists, buyers, and lead farmers.

ARTICLE INFO

Keywords:
UTAUT, technology adoption, sustainable agriculture, horticulture, Albania

JEL classifications:
Q16, O33, Q12, Q18

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Received: 3 October 2025; **Revised:** 15 January 2026; **Accepted:** 18 January 2026.

Introduction

The landscape of Albanian agriculture stands at a crossroads, facing both the promise of technological transformation and the persistent challenges of sustainability, competitiveness, and market integration. The adoption of innovations such as biological pest control and precision farming is increasingly recognised as essential for elevating the quality and marketability of Albania's horticultural products, particularly apples and vegetables, in line with stringent international and EU standards (Arabska, 2021; Schebesta *et al.,* 2020). These sustainable technologies not only improve yields and environmental outcomes but are also seen as vital pathways to economic prosperity for farming communities and as a means of aligning Albanian agriculture with European Union priorities such as the Farm to Fork Strategy and the Green Agenda (Skreli *et al.,* 2024).

At the same time, the adoption of such technologies is increasingly taking place under conditions of heightened uncertainty, where farmers must evaluate innovations in the absence of stable advisory support, reliable performance feedback, and strong institutional guarantees. This raises broader analytical questions about how farmers form adoption intentions in transitional agricultural systems, where standard assumptions of technology diffusion models may not fully hold (Zhllima *et al.,* 2024; Skreli *et al.,* 2024; Imami *et al.,* 2026).

Despite these potential benefits, actual adoption rates for sustainable farming technologies in Albania remain modest, a situation mirrored in other Western Balkan countries. Recent literature highlights both a lack of research and the presence of significant barriers: inadequate extension services, socioeconomic obstacles, and limited adaptation of new technologies to local realities (Androulidakis *et al.,* 2002; Osmani, 2022; Radovanovic and Sanz, 2024; Boshnjaku and Gjeloshi, 2025). These gaps are compounded by the urgent need to understand how farmers perceive, evaluate, and act on innovations, an understanding that is critical not only for policy design but also for practical intervention and market success. The need for robust, context-specific research is especially pronounced in relation to environmental sustainability and climate resilience (Županić *et al.,* 2021; Đokić *et al.,* 2022), as well as the evaluation of how policy initiatives are translated into real outcomes at the farm level.

Importantly, these challenges are not merely empirical or policy-related, but also theoretical. Much of the existing technology adoption literature has been developed and validated in environments characterised by relatively stable institutions, formal training structures, and routinised exposure to innovation. Whether established adoption models retain their explanatory power under the institutional and experiential constraints typical of smallholder agriculture remains an open question.

Theoretically, the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh *et al.* (2016) offers a comprehensive and integrative model for studying technology adoption. UTAUT synthesises key concepts from foundational behavioural models, including the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and Theory of Planned Behaviour (TPB) – and identifies three central determinants of behavioural intention: performance expectancy, effort expectancy, and social influence. These constructs are further shaped by moderators such as age, education, and experience (Blut *et al.,* 2016; Xie *et al.,* 2022).

While UTAUT has demonstrated strong explanatory power across a wide range of organisational and support-rich contexts, its application implicitly assumes relatively low uncertainty, credible performance information, and access to formal advisory support. In transitional smallholder systems, where these conditions are only partially met, the relative importance and functioning of UTAUT's core constructs may differ. Adoption decisions may be driven less by performance-based calculations and more by feasibility considerations and socially mediated trust (Zhllima *et al.,* 2024).

From this perspective, Albanian horticulture is not treated merely as an under-studied national case, but as an analytically relevant setting for examining the boundary conditions of UTAUT. The sector exemplifies a class of transitional smallholder systems in which institutional support and experiential learning remain incomplete, making it a theoretically informative context for reassessing how technology adoption intentions are formed.

Building on this background, the purpose of this research is to investigate *the main determinants influencing the adoption of sustainable innovations among Albanian horticulture farmers.* Rather than assuming the universal applicability of UTAUT relationships, the study explicitly examines how the relative weight of performance expectancy, effort expectancy, and social influence operates under conditions of institutional weakness and early-stage diffusion.

The empirical analysis is based on original data collected from 206 horticulture farmers in key apple and vegetable producing regions of Albania, using a structured questionnaire adapted from the FAO and extended with UTAUT-based items. Exploratory factor analysis (EFA) is employed to validate the measurement of core constructs, while multiple regression analysis assesses the direct and moderating effects of key determinants: performance expectancy, effort expectancy, social influence, and selected demographic variables on farmers' behavioural intentions. This research offers significant contributions at both theoretical and applied levels. By doing so, the study contributes to the refinement of technology adoption theory by clarifying the conditions under which established models such as UTAUT can be meaningfully extended to smallholder-dominated agricultural systems in transition economies.

This paper is structured as follows: Section 2 reviews relevant literature and the UTAUT framework. Section 3 describes the methodology, including data collection and UTAUT construct operationalisation. Section 4 presents the results, and Section 5 discusses the findings. Section 6 concludes with key insights and future research directions.

Literature review

Theoretical Framework

This study applies the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyse technology adoption among Albanian horticultural farmers, as it better addresses the complexities of transitional economies. While earlier models like the Technology Acceptance Model (TAM) (Davis, 1989) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991) focus on individual perceptions, they overlook the crucial role of social, contextual, and institutional factors in collective settings, which are key in smallholder agriculture where peer networks and community norms influence adoption (Blut *et al.,* 2016; Momani, 2020).

UTAUT, as proposed by Venkatesh *et al.* (2016), addresses gaps in earlier models by integrating elements from TAM, TPB, and other frameworks, emphasising not only individual beliefs but also the influence of social networks and enabling conditions. It identifies three key determinants of behavioural intention: performance expectancy (perceived benefits), effort expectancy (ease of use), and social influence (support or pressure from others), while also incorporating contextual moderators such as age, education, and experience, making it adaptable to diverse populations and rural environments (Cao *et al.,* 2023; Xie *et al.,* 2022).

Recent studies in agricultural and transitional economies confirm UTAUT's effectiveness in understanding technology uptake by farmers (Arifin Siregar *et al.,* 2022; Schukat and Heise, 2021; Wang *et al.,* 2023). In these contexts, perceived benefits, ease of use, and social endorsement consistently predict adoption intentions, often surpassing earlier models in explanatory power (Blut *et al.,* 2016; Momani, 2020). UTAUT's adaptability to demographic and contextual variations aligns well with the realities of Albanian horticultural farmers, whose decisions are influenced by collective norms, education, experience, and evolving institutions.

In summary, UTAUT offers a robust and comprehensive theoretical lens for this study, capturing both the psychological and social drivers of technology adoption in a context where traditional, collective, and modernising forces intersect. Its application here not only advances understanding of farmer behaviour in Albania but also contributes to the broader literature on sustainable innovation uptake in transitional agricultural systems.

UTAUT in Transitional Smallholder Systems: Agronomic and Institutional Boundary Conditions

The Unified Theory of Acceptance and Use of Technology (UTAUT) was originally developed and validated in contexts characterised by relatively stable institutional environments, strong advisory support, and routinised exposure to new technologies, such as organisational settings in which users receive formal training and ongoing technical assistance (Venkatesh 2022; Venkatesh *et al.,* 2016). In such contexts, institutional credibility and accumulated user experience reduce uncertainty, allowing expected performance gains to play a central role in shaping adoption intentions. Performance expectancy, the belief that using a technology will improve outcomes, therefore typically emerges as the dominant driver of intention formation in mature adoption environments (Blut *et al.,* 2016; Venkatesh *et al.,* 2016). By contrast, the Albanian horticulture sector exemplifies a transitional smallholder system whose agronomic and institutional features diverge substantially from these assumptions, making it a theoretically informative setting in which to examine the boundary conditions of UTAUT.

Transitional smallholder agriculture in Albania is characterised by fragmented landholdings, weak and uneven extension services, early-stage diffusion of innovations, limited trust in formal institutions, and high levels of experiential uncertainty. Farming structures are dominated by very small, family-operated plots with limited economies of scale and minimal access to formal advisory or technical support. Many sustainability-oriented technologies are still in early diffusion phases, meaning that few farmers have accumulated direct experience and observable outcomes remain scarce. Public extension services are under-resourced, leading farmers to rely heavily on informal or private information channels, particularly agribusiness dealers and input suppliers (Androulidakis *et al.,* 2002). Together, these features create a decision-making environment marked by heightened uncertainty and limited institutional backing.

Under such conditions, the role of performance expectancy may weaken relative to other UTAUT mechanisms. While farmers may broadly agree that a technology is beneficial, fragmented production systems and volatile market conditions can limit their confidence that anticipated gains will materialise on their own farms. When institutional support is weak, the credibility of performance information is reduced, and expected benefits become less effective in differentiating adopters from non-adopters. Prior research demonstrates that when performance beliefs are widely shared but uncertain, their explanatory power diminishes once feasibility and contextual constraints are taken into account (Blut *et al.,* 2016; Venkatesh *et al.,* 2016). In such cases, performance expectancy functions primarily as a legitimising baseline belief rather than a decisive driver of adoption intention. Evidence from agricultural settings similarly indicates that expected economic or agronomic gains are necessary but insufficient to motivate adoption in the absence of experiential feedback and institutional guarantees (Schukat and Heise, 2021).

By contrast, effort expectancy (the perceived ease of learning and using a technology) tends to assume greater importance in institutionally weak environments. Where formal training and extension support are limited, user-friendliness becomes a critical signal of feasibility and manageability. Smallholder farmers facing labour constraints, limited technical skills, and high opportunity costs are more likely to engage with digital tools when they perceive them as simple to learn and compatible with their existing practices (Boshnjaku *et al.,* 2025). In early-stage adoption contexts, perceived simplicity reduces cognitive and operational risk and therefore plays a central role in intention formation (Blut *et al.,* 2016).

Similarly, social influence is expected to play a particularly strong role in transitional smallholder systems. In rural contexts where trust in formal advisory institutions is limited, farmers rely heavily on peers, respected community members, and input suppliers as sources of information and validation. Social influence in these settings extends beyond normative pressure and operates as a mechanism of informational trust, providing experiential reassurance in the absence of formal guidance (Venkatesh *et al.,* 2016).

Taken together, these agronomic and institutional characteristics suggest that UTAUT mechanisms may operate through a different weighting structure in transitional smallholder systems. Rather than being driven primarily by performance-based calculations, adoption intentions are expected to follow a feasibility- and trust-based pathway, in which perceived ease of use and credible social validation dominate early decision-making. Testing UTAUT under these conditions is theoretically relevant because it allows an assessment of the model's boundary conditions beyond the stable, support-rich environments in which it was originally developed, thereby enhancing its applicability to smallholder-dominated agricultural systems in transition economies.

Study hypotheses

Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT), this study examines the psychological and social factors shaping the adoption of sustainable agricultural technologies among Albanian horticultural farmers. UTAUT is widely applied in agricultural and transition-economy contexts for capturing how performance beliefs, perceived usability, and social dynamics interact within smallholder farming systems (Blut *et al.,* 2016; Venkatesh *et al.,* 2016). While the hypotheses follow the standard UTAUT structure to preserve theoretical comparability, this study does not assume that all mechanisms will operate with equal strength. Building on the analytical context of transitional smallholder systems, we expect that institutional weakness and limited experiential learning may alter the *relative importance* of performance expectancy, effort expectancy, and social influence in shaping adoption intentions.

The following hypotheses are proposed.

H1: Higher Performance Expectancy (PE) will be associated with greater Behavioural Intention (BI) to adopt sustainable farming technologies. Performance Expectancy (PE) – the belief that a technology will improve farm outcomes – is consistently identified as a key driver of adoption intentions in agriculture. Empirical evidence from Romania and Vietnam links PE to anticipated productivity gains and willingness to adopt precision technologies (Markovits, 2024; Nguyen *et* *al.,* 2023), while meta-analyses from Asia and Eastern Europe confirm its central role across advanced and emerging markets (Arifin Siregar *et al.,* 2022; Blut *et al.,* 2016; Momani, 2020; Wang *et al.,* 2023).

H2: Greater Effort Expectancy (EE) will lead to a stronger Behavioural Intention (BI) to adopt new agricultural technologies. Effort Expectancy (EE), or perceived ease of use, is a key driver of agricultural technology adoption, particularly in contexts with limited digital literacy or novel technologies (Schukat and Heise, 2021; Xie *et al.,* 2022). Evidence from smallholder and transitional farming systems shows that user-friendly technologies and low disruption to existing practices significantly increase adoption likelihood (Fox *et al.,* 2021; Nguyen *et al.,* 2023; Xu *et al.,* 2023; Cao *et al.,* 2023; Wang *et al.,* 2023).

H3: Higher Social Influence (SI) will positively affect Behavioural Intention (BI) to adopt sustainable agricultural technologies. Social Influence (SI), reflecting encouragement from peers, advisors, and trusted actors, plays a central role in agricultural technology adoption within collective and tradition-bound settings. Empirical evidence from China, Southeast Asia, and Eastern Europe shows that peer and extension endorsement can outweigh perceived utility in shaping adoption decisions (Cao *et al.,* 2023; Nguyen *et al.,* 2023; Markovits, 2024; Xu *et al.,* 2023).

H4: The positive effect of Performance Expectancy (PE) on Behavioural Intention (BI) will be stronger among less-experienced farmers. The moderating effects of farmer characteristics are well-documented in UTAUT studies. Farm experience has been shown to alter the role of performance expectancy. Less-experienced farmers, who may face greater uncertainty, tend to rely more on the expected benefits of technology when deciding to adopt, while experienced farmers may be more self-reliant (Molina-Maturano *et al.,* 2021; Zhang *et al.,* 2024). This dynamic has been observed in Mexico, China, and Central and Eastern Europe, where newer entrants to farming adopt digital or sustainable practices at higher rates if they perceive strong performance benefits (Arifin Siregar *et al.,* 2022; Cao *et al.,* 2023).

H5: The relationship between Effort Expectancy (EE) and Behavioural Intention (BI) will be amplified for farmers with higher levels of education. Education is another important moderator. Numerous studies report that farmers with higher education are more likely to adopt and utilise technologies that are easy to learn and integrate into their workflow (Cao *et al.,* 2023; James *et al.,* 2023; Nguyen *et al.,* 2023; Xu *et al.,* 2023). In Albania and other transition economies, educational attainment correlates with greater openness to innovation and responsiveness to user-friendly technology (Wang *et al.,* 2023; Xie *et al.,* 2022).

H6: The positive effect of Social Influence (SI) on Behavioural Intention (BI) will be stronger for older farmers. Finally, age often interacts with social influence. Older farmers may rely more on established social norms and peer validation before adopting new technologies, whereas younger farmers may be more willing to experiment and adopt independently (Cao *et al.,* 2023; Zhang *et al.,* 2024). This trend is especially pronounced in collective or traditional agricultural systems (Venkatesh *et al.,* 2016).

Together, these hypotheses are grounded in robust empirical evidence from both transitional and developed agricultural settings and highlight the importance of performance beliefs, ease of use, and social dynamics in shaping technology adoption among Albanian horticultural farmers.

Methodology

Sampling and data collection

Data were collected via a structured questionnaire which included items based on the UTAUT model, measuring performance expectancy, effort expectancy, social influence, and facilitating conditions using Likert-scale statements. To examine moderating effects, the questionnaire also gathered demographic data on gender, age, education, and technology experience, as suggested by the theory and prior empirical studies. This structure supports analysis of both the main predictors of adoption and how these effects vary across user groups. Two-stage sampling ensured both relevance and representativeness: first, municipalities with high apple (e.g., Devoll, Korça) and greenhouse vegetable (e.g., Lushnje, Dimal) production were selected; then, within these, villages were chosen and farms selected via random-route sampling. A total of 206 farmers from central and southeastern Albania participated. Two rounds of pilot testing and in-field verification (10% spot-checks) guaranteed clarity and accuracy. Data was collected by trained enumerators who received prior instruction to ensure consistency and accuracy in administering the questionnaire. The survey took place in April to May 2023.

The sampling strategy was designed to be representative of the targeted horticulture subsectors in major producing municipalities rather than nationally representative of all Albanian farmers. Random-route selection within villages reduces enumerator selection bias, but because a complete household roster was not available, formal response-rate estimation and a full non-response bias assessment were not feasible. We therefore interpret results as most generalisable to comparable apple and greenhouse-vegetable smallholder contexts in Albania and similar transitional settings.

Operationalisation of UTAUT constructs

In order to translate our theoretical UTAUT framework into concrete, measurable survey items, we began by mapping each core construct onto specific Likert-scale questions and then validating those items through Exploratory

Table 1: Exploratory Factor Analysis Results.

Rotated Component Matrix[a]		Component	
	Performance Expectancy	Effort Expectancy	Social Influence
I think this new technology would make the job easier (PE1)	0.879		
I think this new technology will have a positive impact on health protection (PE2)	0.914		
I think this new technology would increase the quality of production (PE3)	0.856		
I think this new technology will have a positive impact on the environment (PE5)	0.822		
The new technology for me is clear and understandable (EE1)		0.864	
I find it easy to learn and use this new technology (EE2)		0.903	
I think it's easy for me to get used to new technology (EE4)		0.849	
Those I work with (agronomists/buyers etc.) think I should use new technology (SI1)			0.870
Other farmers I know think I should use new technology (SI2)			0.893
People I trust think I should use new technology (SI3)			0.567

Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalisation; Rotation converged in 5 iterations.
Source: Authors' calculations

Factor Analysis (EFA). At the same time, we identified three demographic moderators – education, farm experience and age – that help explain why the same perceptions might lead to different outcomes across farmers. The following describes how each concept was operationalised.

UTAUT constructs were measured using sets of 5-point Likert-scale items. Behavioural Intention was captured through three statements reflecting farmers' plans and efforts to adopt new technologies, which loaded on a single factor. Performance Expectancy was operationalised as a holistic cognitive belief, consistent with UTAUT applications in agricultural and environmental contexts, capturing farmers' integrated assessment of agronomic, economic, environmental, and health-related performance gains (Venkatesh *et al.,* 2016; Burton, 2004). Environmental benefits were thus interpreted as contributing to long-term farm performance through sustainability and resilience rather than as purely normative outcomes (Edwards-Jones, 2006; Xie *et al.,* 2022). Performance Expectancy was measured using five items assessing expected benefits such as ease of farm work, production quality, cost reduction, health and environmental effects, all loading strongly on a single factor. Effort Expectancy captured perceived clarity, ease of learning, and adaptability of the technology, while Social Influence was measured through four items reflecting encouragement from agronomists, peers, trusted contacts, and family members, forming a cohesive construct.

The Exploratory Factor Analysis (Table 1) confirmed three distinct constructs aligned with UTAUT's original core variables. Performance Expectancy items loaded strongly (0.82–0.91) on a single factor, Effort Expectancy items clustered robustly (0.85–0.90), and Social Influence items grouped together (0.57–0.89), with Cronbach's alphas of 0.89, 0.87, and 0.85 respectively. These high loadings and reliability coefficients demonstrate clear measurement validity, ensuring that subsequent regression estimates rest on sound psychometric footing.

Estimation techniques

We implemented a multiple regression framework to quantify how three core predictors – Performance Expectancy, Effort Expectancy, and Social Influence – shape farmers' Behavioural Intentions. Each predictor was derived from prior Exploratory Factor Analysis, and we included Education, Farm Experience, and Age as interaction terms to capture moderation effects.

We estimated the UTAUT relationships using multiple regression because the study's primary objective is a parsimonious test of main effects and pre-specified moderation in behavioural intention, using construct scores derived from the exploratory factor analysis. This two-step approach (EFA → regression) is widely used in applied UTAUT research when the focus is on structural relationships rather than a full measurement model. In addition, modelling latent-variable interactions in SEM typically requires substantially larger samples and additional assumptions (e.g., identification and distributional choices), which can reduce interpretability in moderate samples. Continuous moderators (Age, Experience, Education) were mean-centred prior to constructing interaction terms to reduce non-essential multicollinearity and to interpret main effects at average moderator levels; heteroskedasticity-robust standard errors and collinearity diagnostics are reported to support stable inference.

The regression equation takes the form:

$$Y = \beta_0 + \sum_{i=1}^{3} U_i + \sum_{j=1}^{3} M_j + \varepsilon \quad (1)$$

where
Y is the dependent variable, which represents the outcome the model seeks to predict or explain. In the context of this study, Y measures Behavioural Intentions of the farmers.
β_0 is the intercept, indicating the expected value of Y when all predictors are at their baseline levels.

U_i are the primary independent variables derived from EFA: Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI).
M_j includes moderators such as Education, Farm Experience, and Age, which interact with the U variables to examine nuanced effects.
ε denotes the error term, capturing unexplained variance in Y.
This approach allowed us to assess both direct effects and nuanced conditional relationships in a single model. Table 2 below summarises the transition from concepts to variables.

Descriptive results

Figure 1 summarises item-level responses for Behavioural Intention (BI), Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI). BI items indicate substantial intention to adopt (e.g., "plan to use"), while "daily use[1]" is lower, suggesting an intention-behaviour gap. EE items score relatively high (e.g., clarity, ease to learn/adapt), and SI is strongest for encouragement from trusted contacts. These patterns are consistent with the regression results below.

Regression results

Table 3 presents the multiple regression results explaining Behavioural Intention (BI), with the model accounting for 49.4% of the variance ($R^2 = 0.494$; adj. $R^2 = 0.474$; $F(9,181) = 20.033$, $p < 0.001$). The analysis shows that Effort Expectancy (EE) is the strongest and most significant predictor ($\beta = 0.486$, $SE = 0.059$), indicating that greater perceived ease and clarity strongly enhance adoption intention. Social

Table 2: Variables in the regression model.

Concept	Variable Type	Measurement/Operationalisation	Symbol
Behavioural Intention	Ratio	Factor score from EFA of three Likert-scale items[a)]	BI (Y)
Performance Expectancy	Ratio	Factor score from EFA of five Likert-scale items	PE (U_1)
Effort Expectancy	Ratio	Factor score from EFA of three Likert-scale items	EE (U_2)
Social Influence	Ratio	Factor score from EFA of four Likert-scale items	SI (U_3)
Education	Ratio	Years of schooling completed by the farmer	Edu
		Interaction: Effort Expectancy × Education	M_1 (EE×Edu)
Farm Experience	Ratio	Years of farm experience	Exp
		Interaction: Performance Expectancy × Experience	M_2 (PE×Exp)
Age	Ratio	Age in years	Age
		Interaction: Social Influence × Age	M_3 (SI×Age)

[a)] Refer to Table 1 for items considered in developing the variables.
Source: own composition

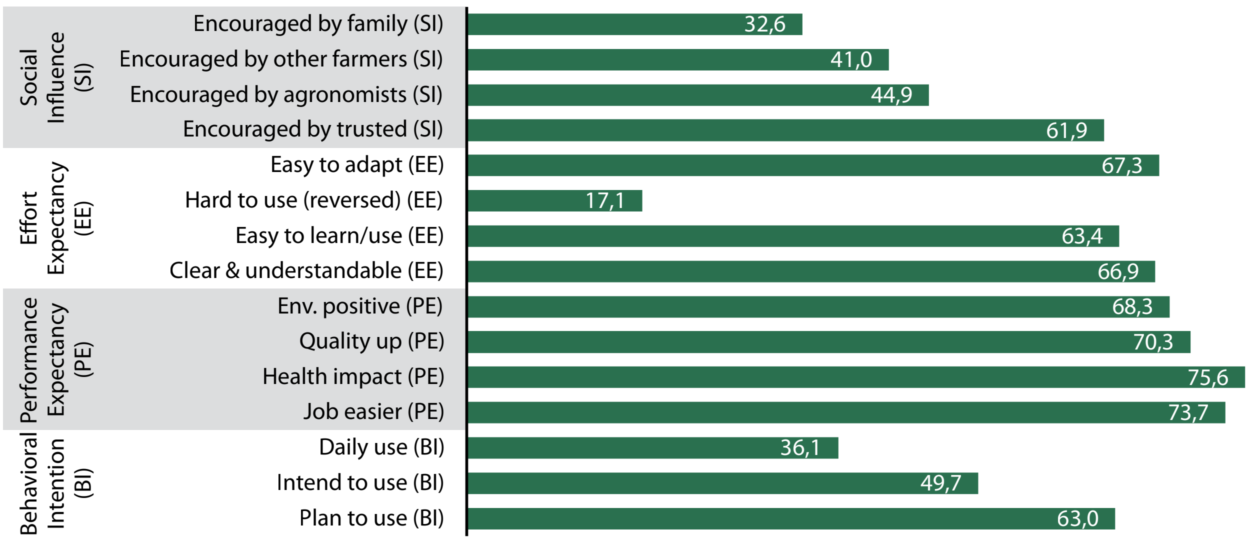

Figure 1: Technology adoption – descriptive statistics.
Note: Values are % agreeing or strongly agreeing (n=206).
Source: own composition

[1] The "daily use" stands for the item "I always try to use new technologies in daily farm management" which is intended to capture habitual and effortful intention to integrate the technology into routine practice, rather than realised or observed behaviour.

Table 3: Determinants of new technology adoption.

	Unstandardised Coefficients β	Standardised Coefficients β	Robust SE	T	Pr(>|t|)	VIF
(Constant)	3.334		0.057	62.555	0.000	
(X_1): Performance Expectancy (PE)	0.074	0.086	0.066	1.15	0.252	2.003
(X_2): Effort Expectancy (EE)	0.486	0.547	0.059	9.4	0.000	1.223
(X_3): Social Influence (SI)	0.200	0.232	0.052	4.189	0.000	1.107
Age	–0.009	–0.146	0.004	–2.399	0.017	1.344
Farm Experience	0.02	0.319	0.005	4.637	0.000	1.714
Education	0.007	0.114	0.004	1.769	0.079	1.501
(M_1): PE*Exp	0.003	0.045	0.005	0.63	0.530	1.832
(M_2): EE*Edu	0.003	0.047	0.004	0.803	0.423	1.221
(M_3): SI*Age	0.004	0.058	0.003	1.061	0.290	1.063

Dependent Variable: BI; Observations: 191; R^2: 0.494; Adjusted: R^2 0.474; Residual Std. Error: 0.630 (df = 181); F Statistic: 20.033*** (df = 9; 181); *p<0.1; **p<0.05; ***p<0.01; Observations are lower than the full sample (n=206) due to listwise deletion for missing values.
Source: own calculations

Influence (SI) also exerts a significant positive effect (β = 0.200, SE = 0.052), suggesting that encouragement from peers, advisors, or trusted contacts raises intention to adopt. In contrast, Performance Expectancy (PE), although positive, is not statistically significant (β = 0.074, SE = 0.066), implying that perceived usefulness does not directly influence intention in this model.

The main regression is estimated on complete cases (n = 191) following listwise deletion of 15 observations with missing values. As a sensitivity check, we compared key demographics between included vs excluded observations and re-estimated the model using multiple imputation; substantive conclusions remain unchanged Appendix Table A4a – included vs excluded comparison; Appendix Table A4b – multiple imputation pooled model.

Turning to covariates and diagnostics, the demographic controls show some effects. Age is negatively associated with BI (β = −0.009, p = 0.017), indicating that older farmers report lower intention to adopt, whereas farm experience is positively associated (β = 0.020, p < 0.001), suggesting that more seasoned farmers report higher intention. Education exhibits a modest, marginally significant coefficient (β = 0.007, p = 0.079). Marginal-prediction plots (Appendix Figure A1–A2) illustrate these effects in substantive terms: predicted behavioural intention increases monotonically with farm experience and decreases with age over a ±10-year range around the sample mean, holding other covariates constant. These predicted effects support the interpretation that experience is associated with higher readiness to adopt, whereas older age is associated with lower intention.

Diagnostics indicate low multicollinearity (all VIFs ≈ 1.1–2.0), and heteroskedasticity-robust standard errors are reported, supporting stable inference. A functional-form sensitivity check adding quadratic terms for Age and Experience does not improve inference (quadratic terms non-significant; results unchanged), so we retain the linear specification for parsimony (Appendix Table A6).

In addition, none of the pre-specified interactions (PE×Experience, EE×Education, SI×Age; i.e., H4-H6) are statistically significant (p = 0.530, 0.423, and 0.290, respectively), implying limited moderation of the core UTAUT relationships by these demographics in this sample. The absence of statistically significant moderation should be interpreted cautiously. First, interaction effects in behavioural models are often small and typically require larger samples for adequate power than main effects. Second, moderator variance may be restricted in this context (e.g., Education is concentrated within a relatively narrow range of schooling years), limiting detectability of slope differences. Third, contextual homogeneity in the sampled subsectors and advisory environment may produce genuinely similar UTAUT pathways across demographic groups.

Robustness checks are reported in Appendix Tables A1–A8 and Figures A1–A5, including incremental model entry (hierarchical build-up), subsector heterogeneity (apple vs greenhouse vegetables), missing-data sensitivity (multiple imputation), functional-form sensitivity (quadratic terms), marginal-effects / simple-slopes plots, and influence diagnostics.

Although none of the pre-specified interaction terms are statistically significant, we provide simple-slopes (marginal effects) plots in the Appendix to visualise that the positive relationships of EE and SI with behavioural intention are broadly stable across age, education, and experience (Appendix Figures A3–A5).

Consequently, two patterns stand out. First, usability (EE) dominates, when technologies are perceived as clear, easy to learn, and adaptable, intention rises markedly. Second, social endorsement (SI) matters, cues from agronomists/buyers and respected peers help convert interest into intention. By contrast, perceived benefits (PE) (though directionally positive) do not clear the significance threshold when EE and SI are in the model. This suggests that in the Albanian horticulture context, removing frictions (how to start, how hard it feels) and increasing social proof carry more weight at the intention stage than reiterating expected performance gains.

We additionally tested whether UTAUT relationships differ by subsector by interacting subsector with the core predictors. The evidence suggests heterogeneity primarily in the role of social influence, whereas performance expectancy remains non-significant across subsectors (Appendix Table A3). This indicates that social endorsement may be more decisive in some production contexts than others, even when the overall pattern of EE and SI dominance is stable.

A RESET test (see Appendix Table A5) suggested potential functional-form sensitivity. We therefore re-estimated the model adding quadratic terms for age and experience (Age^2 and $Experience^2$ see Appendix Table A6). Both quadratic terms were statistically non-significant and substantive conclusions were unchanged (EE and SI remain strong predictors; PE and interaction terms remain non-significant), so we retain the parsimonious linear specification in Table 3.

Discussion

Anchored in the UTAUT framework, the findings indicate that effort expectancy and social influence are the primary determinants of Albanian horticulture farmers' adoption intentions, whereas performance expectancy, although positive, does not remain significant once usability and social endorsement are accounted for. This pattern is theoretically consistent with UTAUT applications in early-stage or institutionally weak adoption contexts, where intention formation is driven less by outcome expectations and more by perceived feasibility and social validation (Venkatesh *et al.,* 2016).

Although Performance Expectancy (PE) displays high descriptive scores, it does not emerge as a statistically significant predictor of behavioural intention once Effort Expectancy (EE) and Social Influence (SI) are included in the regression model. This pattern is well documented in UTAUT-based research and reflects the distinction between shared agreement and explanatory relevance. When most respondents already believe that a technology is beneficial, PE shows limited variance and therefore contributes little to explaining differences in intention (Venkatesh *et al.,* 2016; Blut *et al.,* 2016). In such cases, PE functions as a baseline belief that legitimises the technology rather than a decisive driver of adoption intention. Empirical studies in agriculture and transition economies show that once perceived ease of use and trusted social endorsement are taken into account, performance expectations often lose their independent effect (Schukat and Heise, 2021; Xie *et al.,* 2022; Wang *et al.,* 2023). This suggests that, at the intention stage, farmers prioritise technologies that feel easy to adopt and are socially validated, while expected performance gains remain a necessary but not sufficient condition for adoption.

A related theoretical implication concerns construct boundaries within UTAUT. Prior research shows that effort expectancy may partially absorb variance associated with facilitating conditions, as ease-of-use perceptions are closely intertwined with access to training, technical support, and infrastructure (Venkatesh *et al.,* 2016). Empirical UTAUT studies frequently report high correlations between these constructs, particularly in resource-constrained environments, suggesting that effort expectancy may function as a composite signal of usability, support availability, and adoption risk (Abbad, 2021; Admassu and Gorems, 2024). Consistent with this interpretation, effort expectancy is also theoretically and empirically linked to perceived risk, as technologies perceived as difficult to use are simultaneously perceived as riskier in the absence of reliable institutional backing (Kenesei *et al.,* 2025).

Similarly, the significance of social influence may reflect more than normative pressure. In UTAUT, social influence is expected to be strongest under conditions of uncertainty and limited experience, where individuals rely on others' judgments as informational cues. In contexts with weak formal extension systems, social influence may therefore operate as a functional substitute for missing advisory capacity, with trusted peers, agronomists, and buyers providing validation that formal institutions do not (Cao *et al.,* 2023; Venkatesh *et al.,* 2016). Evidence from decision-support research further supports this interpretation, showing that when technological systems are perceived as unreliable or insufficiently supported, individuals systematically substitute formal guidance with human judgment and social cues (Dietvorst *et al.,* 2015).

Taken together, these findings suggest that in transitional agricultural systems, UTAUT mechanisms operate through a feasibility- and trust-based pathway, where effort expectancy and social influence dominate intention formation, while performance expectancy remains secondary until institutional support and experiential learning are consolidated. This contributes to the UTAUT literature by highlighting how the relative salience of core constructs is contingent on the maturity of advisory and support infrastructures.

Importantly, consistent with the study's design, the results relate to behavioural intention rather than realised technology use. Given the cross-sectional nature of the data, the analysis cannot assess whether stated intentions translate into actual or sustained adoption, and any inference beyond the intention stage should therefore be made with caution.

The non-significance of the three moderation variables suggests that the UTAUT pathways from effort expectancy and social influence to intention are relatively homogeneous across education levels, experience, and age. Nonetheless, the negative main effect of age and the positive main effect of farm experience are informative. Older farmers report lower intention, which may reflect heightened perceived risk or lower willingness to experiment, whereas more experienced farmers report higher intention, possibly because accumulated exposure to technologies and markets reduces uncertainty costs. Together, these patterns imply that repeated, low-risk trials and hands-on learning opportunities may be particularly effective in shifting intentions for older cohorts, while experienced producers can serve as credible demonstrators whose behaviour changes peers' beliefs.

These results have practical implications for the design of programmes and policies that aim to accelerate sustainable technology uptake. Interventions are likely to be more effective when they are structured to make adoption feel easy and socially validated rather than relying primarily on messaging about eventual performance gains. In concrete terms, the findings give rise to a set of reasoned recommendations for policy and programme design, rather than empirically demonstrated mechanisms. Farmer-centred advisory approaches that emphasise stepwise onboarding, short demonstration cycles, and immediate troubleshooting may help lower perceived effort at the intention stage. Likewise, peer-learning formats that engage respected lead farmers, combine demonstration plots with nearby producers, and involve buyer or agronomist endorsement are likely to strengthen social influence. Finally, designing grant or credit schemes that reward verified onboarding milestones (e.g., training completion, correct first-season use, and subsequent peer diffusion) represents a plausible way to align policy instruments with the key behavioural constraints identified by the model. Because family encouragement appears comparatively weaker in the descriptives, including household decision-makers in demonstrations and cost-benefits walk-throughs may help convert stated intentions into routine practice. Overall, when usability and endorsement are the proximate levers, programmes that reduce cognitive load and engineer credible social proof are better aligned with the empirical drivers of intention in this context.

A limitation of this study is that Performance Expectancy was intentionally operationalised as a holistic cognitive construct reflecting farmers' integrated assessment of agronomic, economic, environmental, and health-related performance outcomes. While this approach is theoretically and empirically appropriate in the present context, it does not allow for testing whether instrumental and normative performance considerations exert distinct effects on adoption intentions. Future research could extend this framework by explicitly differentiating these dimensions at the measurement stage to examine whether their relative importance varies across technologies, institutional settings, or stages of adoption.

As the data is cross-sectional, the analysis cannot assess whether stated intentions translate into sustained technology use. Future longitudinal or intervention-based research is therefore needed to examine how and under what conditions intentions evolve into actual adoption. Additionally, future research could estimate a full latent-variable model using SEM or PLS-SEM to account more explicitly for measurement error and to test measurement invariance across groups. Multi-group SEM (e.g., apple vs greenhouse-vegetable producers) would be particularly useful to assess whether the UTAUT pathways differ structurally across subsectors.

Conclusions

This study shows that in transitional smallholder agricultural systems, farmers' intentions to adopt sustainability-oriented technologies are shaped less by anticipated performance gains and more by perceived feasibility and socially mediated trust. Applying the UTAUT framework to Albanian horticulture reveals that effort expectancy and social influence constitute the primary organising mechanisms of adoption intention, while performance expectancy functions largely as a shared baseline belief rather than a decisive driver once usability and endorsement are taken into account.

At a theoretical level, these findings refine UTAUT by demonstrating that the relative salience of its core constructs is contingent on institutional maturity and advisory capacity. In service-constrained contexts characterised by early-stage diffusion and limited experiential feedback, adoption intentions follow a feasibility- and trust-based pathway rather than a performance-calculative one. This contributes to the literature by clarifying the boundary conditions under which performance expectancy loses explanatory power at the intention stage.

From a practical perspective, the results imply that policies and programmes aimed at accelerating sustainable technology uptake should prioritise reducing learning and implementation frictions and strengthening credible social endorsement. Interventions centred on sequenced onboarding, short demonstration cycles, and visible involvement of trusted agronomists, buyers, and respected lead farmers are likely to be more effective than approaches focused primarily on communicating expected benefits.

While the findings are most directly generalisable to smallholder systems in transitional economies with similar institutional characteristics, they underscore a broader insight: without usability and trust, performance promises alone are unlikely to translate into adoption intentions. Future research should follow farmers longitudinally to examine how these intention mechanisms translate into sustained use and explore how facilitating conditions, perceived risk, and intra-household decision-making interact with UTAUT pathways over time.

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Appendix

A1. Cognitive versus calculative evaluation in farmers' adoption decisions

Technology adoption models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) conceptualise adoption decisions as driven by cognitive beliefs rather than by explicit cost–benefit calculations. In UTAUT, Performance Expectancy is defined as a belief about whether using a technology will lead to performance gains, integrating multiple anticipated outcomes into a single subjective judgment (Venkatesh, 2022; Venkatesh *et al.,* 2016). This construct reflects how individuals perceive usefulness, not how they analytically optimise across distinct benefit categories.

Behavioural and agricultural decision-making research further supports this perspective. Farmers are repeatedly shown to rely on heuristic, experience-based, and holistic evaluations, particularly under conditions of uncertainty, complexity, and limited information (Edwards-Jones, 2006). Rather than calculating and weighting individual economic, environmental, or social returns, farmers tend to form integrated beliefs about whether a practice or technology is "good for the farm" overall. In this cognitive framing, environmental outcomes such as soil health, resilience, or reduced chemical exposure are often internalised as long-term performance benefits, rather than treated as separate normative or public-good considerations (Burton, 2004).

This belief-based mode of evaluation is consistent with UTAUT's reflective measurement logic, whereby observed indicators are manifestations of an underlying perception rather than analytically separable components. Accordingly, when empirical evidence shows that farmers do not differentiate between economic and environmental performance indicators, modelling these as a single latent construct is theoretically appropriate and consistent with how adoption decisions are cognitively formed in practice.

A2. Statistical and econometric analysis

Table A2.1: Correlations among key variables

Variable	BI	PE	EE	SI	Age	Experience	Education
Behavioural intentions (BI)	1.000	0.151	0.576	0.121	0.049	0.291	0.392
Performance expectancy (PE)	0.151	1.000	0.000	0.000	0.096	0.311	0.104
Effort expectancy (EE)	0.576	0.000	1.000	0.000	0.022	0.038	0.367
Social influence (SI)	0.121	0.000	0.000	1.000	0.011	–0.185	–0.124
Age	0.049	0.096	0.022	0.011	1.000	0.456	–0.026
Experience	0.291	0.311	0.038	–0.185	0.456	1.000	0.187
Education	0.392	0.104	0.367	–0.124	–0.026	0.187	1.000

Note: Pearson correlations; pairwise complete observations; near-zero correlations among PE/EE/SI are expected because the in PCA/EFA was used orthogonal rotation (Varimax)
Source: own calculations

Table A2.2: Hierarchical (incremental) entry of UTAUT constructs

Panel A: Model fit and incremental contribution

Step / Model	Added at step	R^2	Adj. R^2	ΔR^2	F-change	p-value
Model 1	Controls (Age_c, Experience_c, Education_c)	0.198	–	–	–	–
Model 2	+ Performance Expectancy	0.199	0.182	0.001	0.468	0.495
Model 3	+ Effort Expectancy	0.449	0.434	0.250	90.701	<2e-16
Model 4	+ Social Influence	0.493	0.477	0.044	16.119	8.6e-05

Note: OLS models; n = 191 complete cases; centred covariates; ΔR^2 and F-change from nested-model ANOVA.

Panel B: Key coefficients (B with SE)

Predictor	Model 2 (+PE)	Model 3 (+EE)	Model 4 (+SI)
Performance Expectancy	0.033 (0.060)	0.069 (0.050)	0.053 (0.048)
Effort Expectancy	–	0.482 (0.053)***	0.474 (0.051)***
Social Influence	–	–	0.188 (0.047)***
Age_c	–0.005 (0.006)	–0.008 (0.005)†	–0.010 (0.005)*
Experience_c	0.021 (0.007)**	0.023 (0.006)***	0.027 (0.005)***
Education_c	0.129 (0.027)***	0.046 (0.024)†	0.054 (0.023)*

Significance: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.
Source: own calculations

Table A3: Subsector heterogeneity: pooled interaction model and separate models

Term	B (SE)	p
Performance Expectancy	0.011 (0.157)	0.945
Effort Expectancy	0.444 (0.087)***	<0.001
Social Influence	0.080 (0.080)	0.322
Subsector1 (vegetables)	−0.532 (0.133)***	<0.001
Age_c	−0.006 (0.005)	0.165
Experience_c	0.014 (0.007)*	0.036
Education_c	0.023 (0.025)	0.358
PE × Subsector1	0.006 (0.162)	0.968
EE × Subsector1	−0.047 (0.108)	0.661
SI × Subsector1	0.273 (0.101)**	0.007

Note: Reference group: Subsector = apple (0). Subsector1 = greenhouse vegetables (1); Model fit: $R^2 = 0.559$; Adj. $R^2 = 0.535$; n = 191. Nested-model test (improvement vs pooled no-heterogeneity model): $F(4,180) = 6.721$, p = 4.6e-05.
Source: own calculations

Panel A: Subsector-specific regressions - Apple producers

Predictor	B (SE)	p
Performance Expectancy	0.076 (0.145)	0.600
Effort Expectancy	0.476 (0.084)***	<0.001
Social Influence	0.103 (0.072)	0.157
Age_c	−0.002 (0.009)	0.800
Experience_c	0.007 (0.009)	0.447
Education_c	−0.008 (0.034)	0.811

Note: $R^2 = 0.444$; Adj. $R^2 = 0.389$.

Panel B: Subsector-specific regressions - Greenhouse-vegetable producers

Predictor	B (SE)	p
Performance Expectancy	0.011 (0.054)	0.836
Effort Expectancy	0.388 (0.068)***	<0.001
Social Influence	0.355 (0.065)***	<0.001
Age_c	−0.007 (0.006)	0.213
Experience_c	0.018 (0.011)†	0.091
Education_c	0.040 (0.034)	0.249

Note: $R^2 = 0.456$; Adj. $R^2 = 0.428$.
Source: own calculations

A4: Missing data sensitivity: complete-case vs multiple imputation

Table A4a: Included vs excluded in the complete-case main model

Variable	Excluded (Missing) Mean	Included Mean
Age (years)	52.56	50.39
Experience (years)	NA (all missing among excluded)	17.71
Education (years)	11.67	10.73

Note: Experience is NA for excluded observations because missing experience is one of the reasons observations fail the complete-case rule; this is why we additionally report multiple-imputation estimates (Table A5b); Complete cases: n = 191; excluded due to missingness: n = 15.
Source: own calculations

Table A4b: Multiple imputation sensitivity (m = 20, PMM)

Term	Estimate	SE	df	p
Performance Expectancy	0.034	0.047	193.7	0.462
Effort Expectancy	0.441	0.048	190.5	7.79e-17
Social Influence	0.182	0.046	193.4	9.86e-05
Age (centred)	−0.010	0.005	187.9	0.032
Experience (centred)	0.029	0.005	187.8	1.86e-07
Education (centred)	0.063	0.023	188.6	0.006

Note: Pooled estimates from: BI ~ PE + EE + SI + centred Age + centred Experience + centred Education; Imputation-based estimates confirm the complete-case conclusions: EE and SI remain positive and statistically significant, PE remains non-significant, and age is negative while experience is positive.
Source: own calculations

Table A5. Diagnostics: heteroskedasticity, functional form, influence, and multicollinearity

Panel A: Main-model diagnostics

Diagnostic	Result	Interpretation
Studentised Breusch–Pagan	BP = 16.339 (df=9), p = 0.060	Borderline heteroskedasticity → robust SEs justified
RESET test	RESET = 3.880 (df1=2, df2=179), p = 0.022	Potential functional-form issue → run quadratic sensitivity
GVIF^(1/(2*Df))	PE 1.080; Exp 1.080; EE 1.024; Edu 1.024; SI 1.070; Age 1.070	Very low multicollinearity with interactions
Influential cases (top Cook's D)	# CookD=0.133; #156 CookD=0.103; others smaller	A few moderately influential points, no major issues

Source: own calculations

Table A6: Functional-form sensitivity: quadratic terms

Term	Estimate	HC3 SE	p
I(Age_c^2)	−0.000186	0.000379	0.624
I(Experience_c^2)	−0.000398	0.000473	0.401

Note: Model adds I(Age_c^2) and I(Experience_c^2); HC3 robust SEs shown.
Adding quadratic terms does not change conclusions; neither Age^2 nor Experience^2 is significant, supporting retention of the linear specification for parsimony.
Source: own calculations

Table A7: Simple slopes for the interaction terms (Johnson–Neyman + slopes)

Panel A: PE slopes at Experience_c values

Experience_c level	Slope of PE	SE	p
−1 SD (−10.34)	0.04	0.06	0.51
Mean (≈0)	0.08	0.06	0.19
+1 SD (+10.34)	0.13	0.12	0.26

Panel B: SI slopes at Age_c values

Age_c level	Slope of SI	SE	p
−1 SD (−11.12)	0.15	0.07	0.03
Mean (≈0)	0.20	0.05	<0.001
+1 SD (+10.93)	0.24	0.07	<0.001

Panel C: EE slopes at Education_c quantiles (observed support)

Education_c value	Meaning	Slope of EE	SE	p
−1.77	25% (Edu≈9y)	0.46	0.06	<0.001
−1.77	50% (Edu≈9y)	0.46	0.06	<0.001
+1.23	75% (Edu≈12y)	0.50	0.06	<0.001

Note: The Education quantiles yielded 25% = 9y and 50% = 9y, hence the duplicate Education_c = −1.77.
Even though EE×Education is non-significant, the main effect of EE is strongly positive across observed education levels.
Source: own calculations

Table A8: Alternative operationalisation of UTAUT constructs: composite scores

Term	B (SE)	p
PE_z	−0.092 (0.072)	0.204
EE_z	0.484 (0.058)***	<0.001
SI_z	0.191 (0.053)***	<0.001
PE_z × Experience_c	0.003 (0.007)	0.635
EE_z × Education_c	0.021 (0.024)	0.369
SI_z × Age_c	0.003 (0.004)	0.443

Note: R^2 = 0.493; Adj. R^2 = 0.468; Construct are operationalised as composites instead of factor scores.
Replacing factor scores with item-mean composites yields substantively unchanged conclusions: EE and SI remain positive; PE and all moderation terms remain non-significant.
Source: own calculations

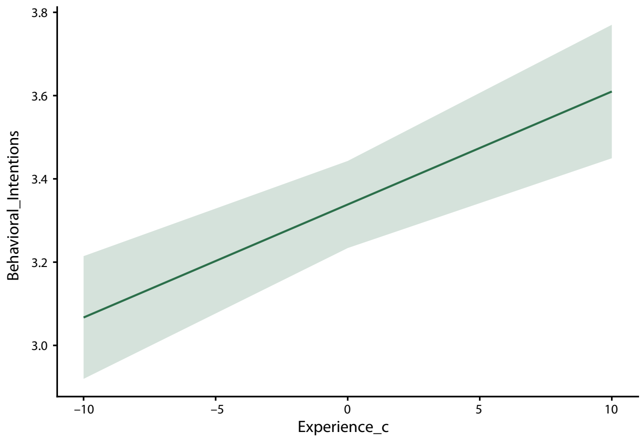

Figure A1: Marginal effect of experience on behavioural intentions.

Note: Line shows predicted values holding other covariates at their means; shaded band indicates the 95% confidence interval.
Source: own calculations

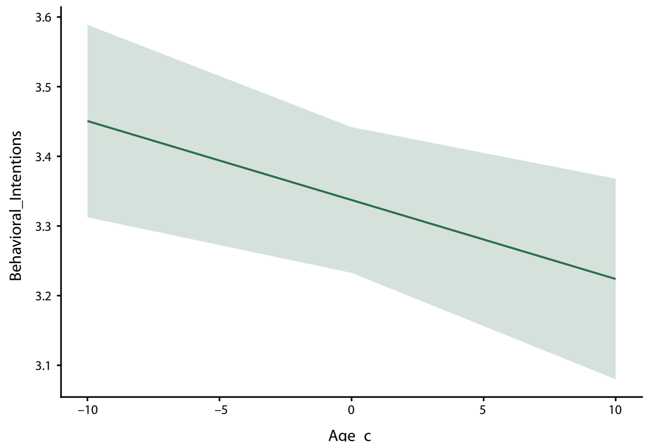

Figure A2: Marginal effect of age on behavioural intentions.

Note: Line shows predicted values holding other covariates at their means; shaded band indicates the 95% confidence interval.
Source: own calculations

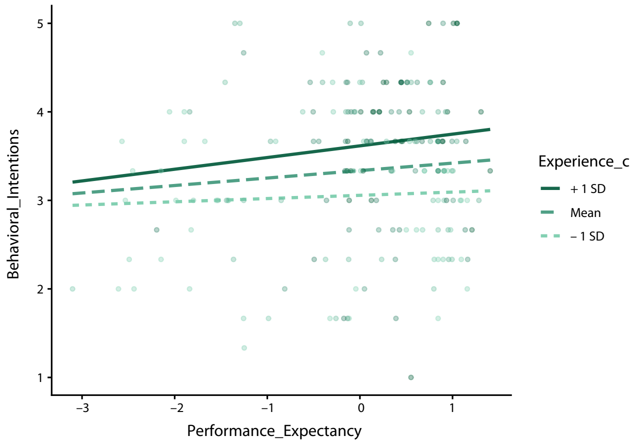

Figure A3: PE ⟶ BI conditional on Experience (−1 SD / Mean / +1 SD).

Note: Lines are model-implied predictions. The interaction term is not statistically significant in the main specification; the plot is shown for interpretability.
Source: own calculations

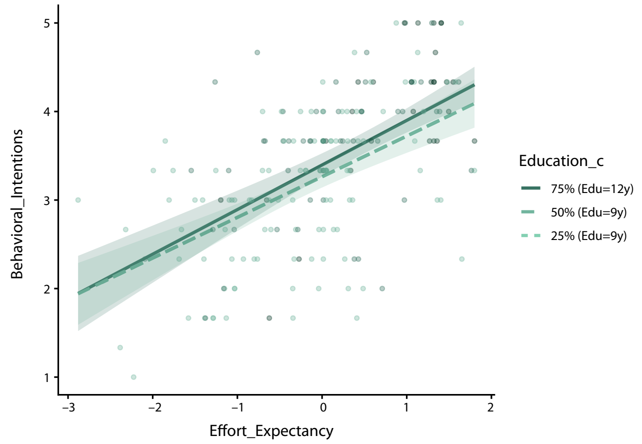

Figure A4: EE ⟶ BI conditional on Education (25th / 50th / 75th percentile).

Lines are model-implied predictions with 95% confidence bands.
Source: own calculations

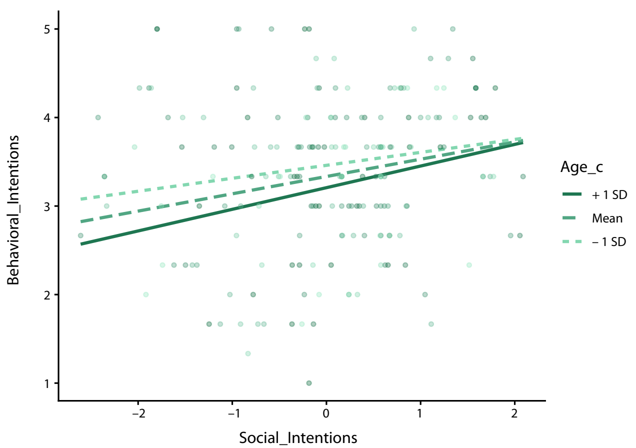

Figure A5: SI ⟶ BI conditional on Age (−1 SD / Mean / +1 SD).

Note: Lines are model-implied predictions. The interaction term is not statistically significant; the plot is shown for interpretability.
Source: own calculations