

From AI-personalized learning to green purchasing: A TPB-S-D logic pathway via self-regulated learning, perceived knowledge gain, and attitudes in Jordan and Palestine

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ABSTRACT

Sustainable consumption requires more than awareness; it requires learning that reshapes everyday habits. Evidence remains limited on whether personalized learning enabled by artificial intelligence produces gains that transfer to greener purchasing, especially in developing contexts. We address this gap by testing a learning-to-consumption pathway that links personalization to green purchasing through self-regulated learning, perceived knowledge gain, attitudes, and intentions. Grounded in the theory of planned behavior and self-regulated learning, and interpreted through service-dominant logic, we conceptualize personalized learning as a platform-mediated service that co-creates knowledge as an operant resource. We treat platform governance, including access conditions, data protection, accountability, and algorithmic transparency, as boundary conditions that shape platform use and trust. Using cross-sectional survey data from 750 university students in Jordan and Palestine, we estimate the proposed indirect effects using partial least squares structural equation modeling. Results support a sequential indirect pathway from personalization to green purchasing via self-regulation, perceived knowledge gain, attitudes, and intentions. The study integrates educational psychology with consumer behavior, extends evidence from underrepresented settings, and indicates that sustainability benefits from educational technology depend on reliable connectivity and responsible data governance.

Keywords: AI-personalized learning; Self-regulated learning; Theory of planned behavior; Green purchase behavior; Service-Dominant Logic; Sustainability education

1. Introduction

Sustainable consumption is the focal point of the debate in the field of education and management. However, the question still persists: Does education really influence daily consumption habits? What is not being discussed is whether the personalization of learning using artificial intelligence could influence daily consumption habits. The use of artificial intelligence in the personalization of learning seems to be promising in this regard. Personalization in learning can be achieved by using artificial intelligence, as it can be aligned with the learning progress of the student [1]. This will, in turn, increase the motivation of the student to learn, as they will be able to learn and manage themselves strategically. Adaptive learning, as mentioned earlier, provides learners with information on sustainable consumption, but it also allows learners to learn to self-regulate their learning by providing them with the necessary information and guidance [2]. This will, in turn, help learners who are not as prepared to develop learning habits and will be able to push themselves to learn and complete tasks that they find difficult. The question of whether the benefits of learning and the agency learners develop in the classroom can influence their consumption habits prompts the discussion of learning transfer to consumption.

The AI-driven PL is a platform that is organized through a set of algorithms and an associated infrastructure, and it is not merely an extension of the classroom. The governance of the platform refers to the set of rules that govern data use, targeting, and oversight. The data protection refers to the limits set on the use of

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personal data, including data collection, processing, and sharing. The accountability standards refer to the set of rules that determine who is accountable in cases of harm [3]. These factors are important because personalization is associated with connectivity and profiling. In Palestine and Jordan, personalization is associated with fair learning outcomes and effectiveness through access and affordability, as well as legal data exchange and transparent profiling [4]. Governance, therefore, is not merely an ancillary contribution but a boundary condition that determines whether students will be able to use the platform consistently and whether feedback is credible and perceived as such. Credibility is a factor that determines how learning outcomes will be internalized and used. In this model, the governance of personalization contributes to capacity development, self-regulation, and perceived knowledge gains, which translate to cognitive capital that is transferable beyond the classroom and learning environment [5]. Such learning outcomes can translate to market-oriented mindsets and environmentally sustainable consumption behaviors.

In the Theory of Planned Behavior, environmentally friendly behavior relies on attitude and intention, not information as such; it is knowing that matters when it has been taken in by a positive assessment of the action and a strong intention to implement it [6]. That is, awareness is only useful when it is complemented by a positive evaluation of the behavior and an actual intention to act on it. This influence is seen in more recent research, which indicates that environmental knowledge is only effective when accompanied by positive attitudes and perceptions [7]. Meta-analytic results also see attitudes as among the strongest predictors of green buying intentions [8]. Building on this convergence, we link educational and behavioral perspectives in a pathway where an AI-personalized learning experience strengthens self-regulated learning and perceived knowledge, which in turn nurture pro-green attitudes, reinforce intentions, and culminate in more sustainable purchasing. This pathway is policy addressable; its strength depends on conditions, access, affordability, data protection, and transparency, which shape how platform-mediated learning translates into market behavior.

This study addresses several gaps. First, the literature rarely connects personalized learning with downstream, environmentally responsible purchasing; it remains unclear whether improvements in students' learning processes carry over into consumer decisions. Second, mainstream TPB models seldom incorporate internal learning factors, self-regulated learning, and perceived knowledge gain, treating knowledge, if at all, as a background condition rather than a driver of attitudes and intentions [6], [7]. By integrating SRL and knowledge acquisition into the attitude behavior pathway, we extend TPB to explain how learning can shape sustainable consumption. Third, evidence from developing contexts is scarce; most studies on green purchase intentions draw on Western or East Asian samples, leaving it uncertain whether TPB and SRL relations generalize to different cultural and socio-economic settings. Focusing on university students in Jordan and Palestine helps fill this gap. Ultimately, a policy-oriented gap exists, which transcends pedagogy and educational psychology. Previous research has rarely addressed the question of the governance of the platform, which is conceptualized as the rules governing the operation of the platform, as well as the data policy conditions in which artificial intelligence-driven personalization is related to pro-environmental attitudes. It has also rarely addressed how this is translated into intentions, or the extent to which it is independent of the influence of instruction design versus the regulation of telecommunications access and data sharing. By situating our model in a cross-border emerging-market setting and articulating these governance contingencies, we speak directly to policy audiences concerned with the societal externalities of AI-mediated platforms.

The study offers three related contributions that have implications for theory and practice. First, it links self-regulated learning and the theory of planned behavior to explain how learning outcomes translate to green purchasing through perceived knowledge gain, attitudes, and intentions [2]. Second, it conceptualizes AI-personalized learning as a service process in which knowledge is co-created, not merely transmitted, and aligns with the service dominant logic [9]. Third, it tests this model in the contexts of Jordan and Palestine, in which factors such as connectivity and data governance shape the use of the platform and influence trust, thereby conditioning the translation from learning to market choice [6]. These contributions of the study help to shed light on the conditions under which investment in AI platforms translates to benefits beyond academic outcomes and lay the groundwork for considering the implications of governance.

We view AI-enabled learning as a regulatable infrastructure, characterized by access rules, data governance, and personalization policies. These specifications drive self-regulation and sensed knowledge to pro-sustainability orientations and inclinations. Emphasizing actionable levers, clear data practices, robust privacy defenses, and access for everyone, the paper discusses the social and market effects of platforms and digital policy, and not pedagogy alone. If AI-personalized learning consistently enhances self-regulation and perceived knowledge, proximal determinants of pro-environmental attitudes, then telecommunications and platform governance are public value tools. The policy agenda is straightforward: increase low-cost, high-quality access; require transparent, layered disclosure of data capture, personalization logic, and significant opt-out or portability; and encourage evidence-based platform design that translates learning gains into sustainable consumption. The cross-country findings provide policy-relevant benchmarking to regulators and suppliers who wish to balance personalization with sustainability targets.

A cross-sectional survey of university students in Jordan and Palestine was carried out. The suggested pathway was tested with partial least squares structural equation modeling. This analysis identifies the chain of effects from AI-Personalized Learning to self-regulation, and then on to perceived knowledge gains and attitudes/intentions, and green purchasing. The two-country sample helps ensure the results have higher regional and external validity. It also tests the generalizability of the TPB processes in a developing context. The research question is quite simple: Does AI-Personalized Learning indirectly predict green purchasing through self-regulation, perceived knowledge gains, attitudes/intentions in Jordan and Palestine?

2. Literature review

Sustainable consumption then emerged as a priority, again raising the question of whether or not educational innovation can foster dispositions to inform more sustainable decision-making. AI-facilitated personalization tailors content and feedback to the student, not only the manner in which knowledge is built, but also the manner in which it keeps students engaged during self-study. When learning is attuned to rate and achievement, motivation and strategic regulation tend to be improved [10], [11]. Reasoned action principles of consumer behavior remind us that knowledge impacts behavior through the mediation of intention, which in turn is founded on positive attitudes [6]. From consumer behavior, reasoned action principles remind us that knowledge shapes conduct through intention, itself grounded in favorable attitudes [7]. Bringing these strands together, we propose a framework that links an AI-personalized learning experience to green purchasing through a sequence of psychological constructs. The argument rests on three pillars: self-regulated learning, planning, monitoring, and reflection [2]; the theory of planned behavior, behavior guided by intention formed by attitudes alongside norms and perceived control [6]. Service-dominant logic views knowledge as an ‘operant resource’ that is co-created through use and interaction [9]. In this regard, AI-personalized platforms function as ‘knowledge co-creation services’ that facilitate learning outcomes that have the potential to shape consumer attitudes and, in turn, intentions in the sustainability domain. Simultaneously, these platforms function as ‘governable digital infrastructures’ in that their effects depend on the rules governing access, data governance, data use, targeting, oversight, and personalization.

We advance a linked sequence of hypotheses. First, an AI-personalized learning environment is expected to strengthen students’ self-regulatory capabilities. Second, stronger self-regulation should foster greater perceived knowledge gained from the learning experience. Third, this perceived knowledge is anticipated to shape more favorable attitudes toward green purchasing. Fourth, more favorable attitudes should, in turn, heighten the intention to buy green products. Finally, those intentions are expected to manifest in actual purchasing choices that favor environmentally responsible options. In what follows, we review the literature that supports each step in this chain, clarifying the theoretical logic, surveying the available evidence, and pinpointing the gaps this study addresses. We also note that the strength of each link is likely to depend on platform governance and telecommunications conditions, access and affordability, data protection safeguards, and transparency of personalization, which shape how learning gains are formed, trusted, and translated into market behavior.

2.1. AI-Personalized learning and self-regulated learning

Personalized learning denotes instructional systems that tailor content and feedback to the individual, often through AI that optimizes the match between materials and learner needs. Two modes are common: adaptivity, in which the system autonomously adjusts the experience, and adaptability, in which learners themselves shape features of the task or pacing [11]. Both aim to deliver appropriate challenge, guidance, and resources while honoring learners' pace and preferences, thereby deepening their engagement in managing their own study. By supplying targeted scaffolds and timely feedback, adaptive systems can help students clarify goals, monitor understanding, and revise plans, core processes of self-regulated learning [2], [12]. AI-enabled tutors operationalize these supports by issuing hints or adaptive prompts when learners struggle, boosting immediate performance and strengthening metacognitive approaches for future tasks [10]. Empirically, personalization improves learning effectiveness and can expand learner autonomy: a meta-analysis in higher education shows that adaptivity enhances outcomes via performance contingent scaffolding, while adaptability fosters engagement by drawing students into decisions about their learning [11]. In the context of this journal, these benefits are governance contingent: their realization depends on access and affordability, protections for learner data, and transparent rules for algorithmic personalization.

Research suggests that personalization does not merely serve to display content; it teaches learners how to learn by eliciting responses to adaptive stimuli and encouraging thoughtful decisions around pace and strategy. Reports from teachers and research into digital learning show that personalization in feedback, from adaptive hints to customized views of progress, increases motivation and encourages thoughtful use of strategy [13]. Intelligent tutor research also finds that need-contingent, just-in-time support encourages appropriate help-seeking and problem-solving behavior [10], in keeping with social cognitive accounts whereby supportive contexts model and facilitate strategic action. Meta-analyses establish that self-regulated learning is responsive to change: goal-directed training and assistance enhance planning, monitoring, and control [14], [15]. More competent self-regulators succeed in web-based higher education, but less competent self-regulators struggle with no support; tailored e-learning can provide the support and individualized attention that lead learners to develop more competent strategies and bridge performance gaps [1], [16]. The realization of these gains is governance-contingent: equitable access, credible data safeguards, and transparent personalization rules are prerequisites. Accordingly, we expect AI-personalized learning to have a positive effect on students' self-regulated learning.

H1. Perceived AI-personalized learning (the instructional personalization or fit delivered by the platform) positively affects students' self-regulated learning (SRL).

2.2. Self-regulated learning and perceived knowledge gain

Once students engage in effective self-regulated learning (SRL), the next issue is whether this translates into perceived knowledge gain (PKG), students' own judgment of how much their understanding has advanced. PKG matters because it covaries with objective learning and satisfaction [17], [18]. A consistent literature shows that learners who set goals, deploy appropriate strategies, and monitor progress achieve more and report greater learning than those who do not [1]. In online and technology-enhanced settings, SRL is especially consequential: meta-analytic and review evidence links SRL training to improvements in achievement and strategy use [14], [15]. Studies during the shift to remote instruction associate SRL with related internet self-efficacy with higher satisfaction and perceived gains [18], [19]. cycles of planning, monitoring, and adaptive revision strengthen encoding and integration with previous experience more profoundly, supporting learners' feeling that true learning has occurred [2]. Empirical work on intelligent and adaptive systems likewise suggests that structured prompts and learner control encourage SRL and confidence in what has been learned [16], [20]. These benefits are governance-contingent: they depend on reliable access, credible data safeguards, and transparent personalization rules that enable students to engage fully with platform features. Accordingly, we expect higher SRL to be associated with higher PKG when interacting with an AI-personalized learning platform.

H2. SRL positively increases perceived knowledge gain (PKG) from the platform.

2.3. Perceived knowledge gain and attitude toward green purchasing

Our model links the educational and consumer domains by proposing that gains in learning translate into attitudes toward green purchasing, an overall evaluation of buying environmentally friendly products. The premise that knowledge shapes attitude is well established in psychology and environmental education, even if the relationship is not always linear: awareness is typically a prerequisite for concern and favorable assessments of pro-environmental acts [21]. When learners grasp the impacts of consumption and the benefits of greener options, attitudes shift in a positive direction. Evidence from large student samples indicates that more intensive environmental education enhances knowledge, which in turn correlates with stronger pro-sustainability attitudes and increased awareness of responsible consumption, particularly when instruction explicitly addresses consumerism [22]. In our setting, perceived knowledge gain from the AI-personalized platform plausibly includes sustainability-relevant understanding; as students recognize what they have learned, they become more convinced of the importance and efficacy of green purchasing. Empirical work supports this knowledge in the attitude pathway: environmental knowledge functions as a distal driver that influences behavior through attitudes and intentions [7]. Meta-analytic evidence highlights complementary drivers, such as perceived value and trust, which themselves depend on what consumers know [23]. Studies in developing contexts report similar patterns: knowledge improves attitudes, which then bolster intentions [24]. Cognitive-consistency logic provides a parallel rationale: people seek to align actions with what they know. While other forces, values, and social influences also matter [25], we focus on newly acquired knowledge as the proximal attitudinal driver produced by the learning experience. The strength of this link is governance contingent: access, affordability, data protection, and transparent personalization shape whether platform-mediated knowledge gains are formed, trusted, and converted into favorable attitudes toward green purchasing.

H3. PKG positively influences attitude toward performing green purchasing.

2.4. Attitude toward green purchasing and green purchase intention

Within the Theory of Planned Behavior, attitude is the primary antecedent of behavioral intention [6]. Applied to sustainability, a more favorable attitude toward buying green products should yield stronger green purchase intention. This proposition is well supported: TPB-based studies consistently report a positive attitude intention link across markets and product categories [26], [27], and meta-analytic evidence confirms a robust, often dominant, effect of attitude on green purchase intention [8]. Findings in tourism, hospitality, and transport echo the same pattern: those who view pro-environmental options positively are more inclined to plan such choices [28]. While perceived behavioral control and social norms can also matter, attitude typically exerts the largest weight in eco-intention models [29]. Our model, therefore, treats attitude as the key proximal driver of intention among students considering green purchases. We note that the formation and salience of this attitude can be conditioned by platform governance and telecom factors, access and affordability that enable meaningful use, and data governance and transparency that sustain trust in platform-mediated learning, thereby shaping how learning-driven attitudes convert into intention.

H4. Attitude toward performing green purchasing positively predicts green purchase intention (GPI).

2.5. Green purchase intention and actual green purchasing behavior

In the Theory of Planned Behavior, intention is the immediate antecedent of behavior, capturing the motivation and resolve to act [6]. Applied here, stronger green purchase intention (GPI) should predict subsequent green purchasing behavior (GPB). A large body of evidence supports this linkage while acknowledging an “intention behavior gap”: intentions explain meaningful but incomplete variance in action [30], and interventions that raise intentions tend to raise behavior with moderate effect sizes [31]. Habit and context moderate the link; past behavior can dilute intention’s predictive power [32], and situational affordances such as availability, convenience, and cost shape enactment [33]. Sectoral studies in green consumption echo the core prediction: favorable intentions translate into higher odds of purchasing green [26]. Implementation intentions, concrete plans for when, where, and how, further strengthen conversion from intention to action [34]. We note that the

salience and enactment of intention are governance contingent: equitable connectivity, trustworthy data practices, and transparent personalization can reduce friction and bolster follow-through in platform-mediated settings. Given our longitudinal design, we directly test whether students with stronger GPI are more likely to report GPB over time; accordingly, we hypothesize a positive intention-behavior relationship.

H5. GPI positively predicts actual green purchasing behavior (GPB) during the follow-up period.

2.6. Research gaps and contribution of the study

We synthesize SRL, TPB, and S-D Logic to test a single pathway from AI-personalized learning to green purchasing, an integration missing from prior work that has focused on learning outcomes alone [11], [13]. By inserting perceived knowledge gain as the proximal attitudinal driver [7] and modeling the platform as a co-creation service [9], we link educational gains to market-relevant dispositions. Studying students in Jordan and Palestine fills a regional gap and probes generalizability beyond Western/East-Asian samples [26], [35], [36], [37]. We treat the pathway as policy-addressable, conditioned by access, affordability, data protection, and algorithmic transparency that govern whether platform-enabled learning translates into sustainable consumption. These hypothesized causal relationships are presented visually in Figure 1.

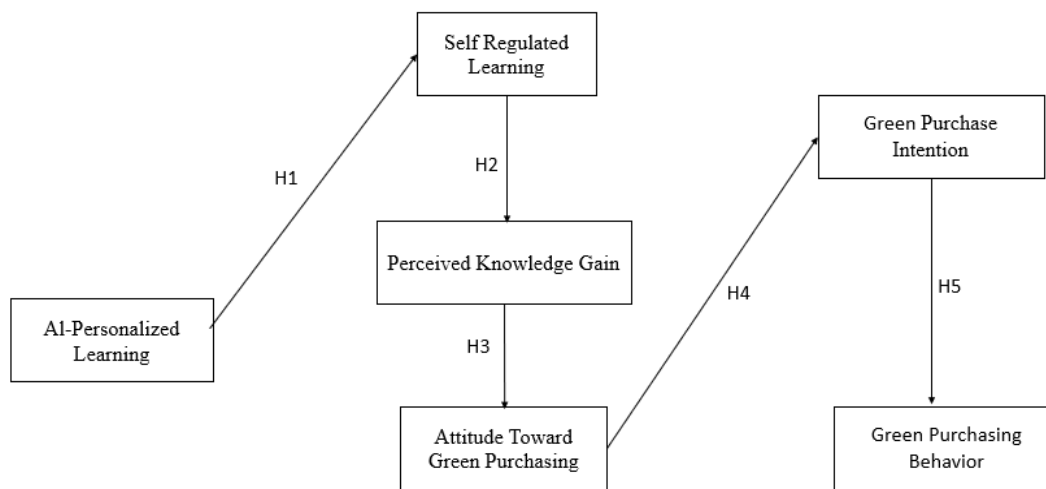


Figure 1. Hypothesized model

3. Materials and methods

3.1. Sampling

We used a cross-sectional survey of university students in Jordan and Palestine (West Bank), recruiting from multiple public and private institutions to capture variation in academic disciplines and demographics. Because of access constraints brought about by conflict, no response came from Gaza; the Palestinian sample, therefore, reflects only West Bank universities. The two-country study increases cultural representation and responds to calls for more Middle Eastern evidence on sustainable models of behavior [36], [37]. Institutional review board approval was initially obtained, and all participants provided informed consent according to international ethics standards. In total, 750 valid questionnaires were analyzed (500 Jordan; 250 West Bank). The heterogeneity of institutions and student profiles supports examination of the framework's reliability across subgroups [35], [38]. The larger Jordanian subsample reflects easier field access, whereas the smaller Palestinian subsample reflects the constraints noted; nonetheless, both groups are sufficiently sized for independent statistical inference. We highlight that the platform-mediated learning context, and thus engagement with the constructs studied, takes shape within differing telecom and governance environments across the two settings, an aspect we consider in interpreting results.

Given the model's complexity and multi-group structure, the achieved sample is adequate for structural equation modeling. SEM is well-suited to testing theory-driven relationships among latent constructs [6], and stable parameter estimates typically require sizable samples; methodological guidance commonly cites a lower bound

near two hundred cases, with larger numbers advised for complex or multi-group models. Our total of 750 respondents, with each national subgroup exceeding two hundred, comfortably meets these benchmarks and supports precise estimation as well as subgroup comparisons. Related meta-analytic and cross-cultural work similarly emphasizes robust samples to detect modest effects and to assess generalizability [32]. In sum, our sampling strategy and realized size provide a rigorous foundation for model testing and validation. The multi-group design also enables policy-relevant contrasts under differing connectivity and data-governance conditions, strengthening the external relevance of the findings.

3.2. Measurement instrument

SEM provides a principled way to estimate theory-based relations among latent constructs and observed indicators. The workflow proceeds from data screening to CFA, assessing reliability, validity, and fit, then to the structural model [32]. Valid application depends on familiar assumptions regarding specification, sample adequacy, and distributional properties [39]. Here, SEM's multi-group capabilities allow policy-relevant comparisons across distinct telecom and data-governance environments.

SEM rests on familiar conditions. Linearity is assumed, since parameters are estimated with linear procedures. Multicollinearity should be low enough to avoid unstable or inflated coefficients; correlated predictors can be modeled, but near-perfect overlap undermines identification. Sample size must be adequate for stable estimation and power; common guidance suggests several hundred observations for models with multiple latent variables and about a dozen indicators, with rules-of-thumb placing minimums in the low hundreds for typical applications. Measurement should be sufficiently redundant: at least three indicators per latent construct are preferred to reduce error and raise reliability, though two indicators can be defensible when strongly constrained or embedded in a well-identified system. In a multi-group setting, as in our cross-country, platform-mediated context, these conditions should hold within each group, given potential differences in connectivity and data-governance environments that can affect item functioning and collinearity.

4. Data analysis results

In Figure 2, a structural equation modeling (SEM) diagram created with SmartPLS4, a program for partial least squares (PLS) analysis, is depicted. SEM is a potent statistical method for examining intricate connections between latent and observable variables.

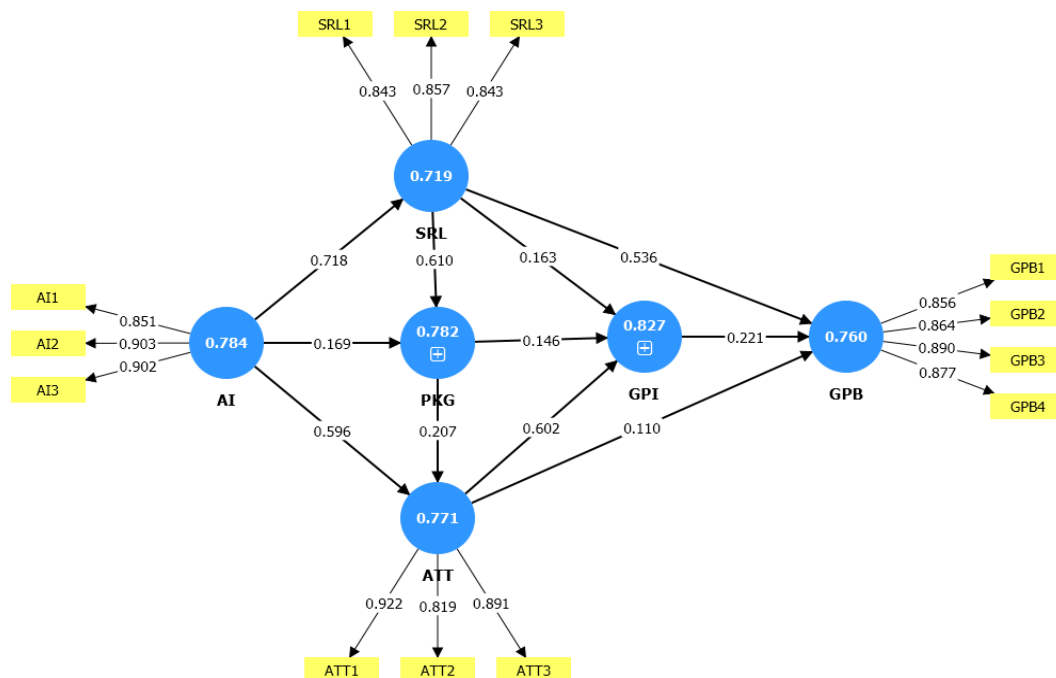


Figure 2: The measurement model (AI personalized learning (AI), students' self-regulated learning (SRL), perceived knowledge gain (PKG), attitude toward performing green purchasing (ATT), green purchase intention (GPI), green purchasing behavior (GPB))

In PLS-SEM, the measurement (outer) model evaluates how well latent constructs are captured by their indicators before any inference about structural paths. For reflective blocks, indicator reliability is judged by outer loadings ideally ≥ 0.70 ; items below this threshold warrant scrutiny or removal. Internal consistency is then assessed using Cronbach's α (acceptable from ~ 0.70 , with ~ 0.60 sometimes tolerated in early stages), composite reliability (CR) (target $0.70\text{--}0.90$), and Dijkstra–Henseler's ρ_A (≥ 0.70). Convergent validity is supported when the average variance extracted (AVE) ≥ 0.50 , and discriminant validity by HTMT (preferably $< 0.85\text{--}0.90$) and clean cross-loadings. Only after these criteria are met should the structural (inner) model be interpreted; path coefficients concern relations among constructs, not measurement quality. Although our analysis focuses on reflective specifications, formative blocks, when theoretically justified, require weight significance, collinearity checks, and content validity rather than high loadings. Given our cross-country design, we also verify measurement invariance (e.g., MICOM) so that observed differences are not artifacts of unequal measurement, where connectivity and data governance conditions can shape item functioning.

Indicator reliability is first assessed by the outer loading, the correlation between an indicator and its latent construct. The goal is to maximize these loadings so that subsequent structural inferences rest on well-measured constructs. Loadings ≥ 0.70 are preferred; values in the $0.40\text{--}0.70$ range can be retained when overall AVE and CR remain satisfactory, and theory supports the item's content. Indicators with loadings < 0.40 are typically candidates for removal unless there is a compelling theoretical justification. In multi-group applications, these decisions should be replicated within each group, given that connectivity and data-governance differences may affect item functioning.

Convergent validity in Table 1 is indicated when each construct explains at least half of its indicators' variance, $AVE \geq 0.50$, and reliability indices are satisfactory. Discriminant validity requires that constructs be empirically distinct; a common check is the Fornell-Larcker criterion, where the square root of a construct's AVE exceeds its correlations with other constructs. To guard against redundancy and unstable estimates, examine multicollinearity (e.g., $VIF < 5$ at the indicator or predictor level). In our cross-country application, these thresholds are evaluated within each group and supplemented by invariance tests to ensure comparability under differing connectivity and data-governance conditions..

The provided Fornell-Larcker matrix helps analysts evaluate discriminant validity in Smart-PLS SEM analysis as an important assessment tool for research. Discriminant validity confirms that model-based latent constructs maintain unique identification from other constructs in the analysis.

Table 1: Fornell-Larcker criterion

Construct	AI	ATT	GPB	GPI	PKG	SRL
AI	0.886					
ATT	0.721	0.878				
GPB	0.617	0.660	0.872			
GPI	0.669	0.799	0.679	0.909		
PKG	0.607	0.569	0.735	0.608	0.884	
SRL	0.718	0.697	0.765	0.690	0.732	0.848

Beyond the Fornell-Larcker check, in Table 2 we evaluated discriminant validity with the heterotrait-monotrait (HTMT) ratio, a more sensitive test of construct distinctiveness in PLS-SEM. All HTMT estimates were below the conventional .90 threshold [41], indicating clear separation among AI-personalized learning (AI), self-regulated learning (SRL), perceived knowledge gain (PKG), attitude toward green purchasing (ATT), green purchase intention (GPI), and green purchasing behavior (GPB). This supports good discriminant validity and, by extension, lends credibility to the interpretation of structural paths. Given the cross-country design, such

distinctiveness also strengthens the policy relevance of the results: it suggests that the measured mechanisms remain separable under differing connectivity and data-governance conditions.

Table 2: Heterotrait-monotrait ratio (HTMT) - matrix

Construct	AI	ATT	GPB	GPI	PKG	SRL
AI	-					
ATT	0.834	-				
GPB	0.696	0.743	-			
GPI	0.745	0.895	0.732	-		
PKG	0.684	0.633	0.812	0.658	-	
SRL	0.862	0.834	0.894	0.791	0.855	-

In Table 3, both outer loading, AVE analysis, discriminant validity and reliability indices will be investigated for the 6 constructs for measurement properties: AI personalized learning (AI); students' self-regulated learning (SRL); perceived knowledge gain (PKG); attitude toward performing green purchasing (ATT); green purchase intention (GPI); and green purchasing behavior (GPB). These measures will be evaluated for construct validity and reliability in a structural equation modeling environment.

Table 3: Measurement properties of (AI personalized learning (AI), students' self-regulated learning (SRL), perceived knowledge gain (PKG), attitude toward performing green purchasing (ATT), green purchase intention (GPI), green purchasing behavior (GPB))

Construct	Items	Convergence validity		Discriminant validity	Reliability	Cronbach's alpha	
		Outer loading	Average variance extracted (AVE)				
AI	AI1	0.851		YES	0.863	0.862	
	AI2	0.903	0.784				
	AI3	0.902					
ATT	ATT1	0.922		YES	0.869	0.851	
	ATT2	0.819	0.771				
	ATT3	0.891					
GPB	GPB1	0.856		YES	0.901	0.895	
	GPB2	0.864	0.760				
	GPB3	0.890					
	GPB4	0.877					
GPI	GPI1	0.913		YES	0.933	0.930	
	GPI2	0.897	0.827				
	GPI3	0.911					
	GPI4	0.916					
PKG	PKG1	0.843	0.782	YES	0.912	0.935	0.907

Construct	Items	Convergence validity		Discriminant validity	Reliability		
		Outer loading	Average variance extracted (AVE)		Fornell-Larcker Criterion: is the square root of AVE for each construct be greater than its correlations with other constructs?	Composite reliability (rho_a)	Composite reliability (rho_c)
	PKG2	0.921					
	PKG3	0.869					
	PKG4	0.902					
	SRL1	0.843					
SRL	SRL2	0.857	0.719	YES	0.805	0.885	0.804
	SRL3	0.843					

All the measures show reliable performance and demonstrate valid relationships with one another. The AI construct demonstrates adequate explanation of indicator variance through its outer loadings, which range from 0.851 to 0.903 and its AVE value of 0.784. Reliability tests show strong consistency between variables through composite reliability calculations and Cronbach's alpha results: rho_c equals 0.916 and rho_a equals 0.863, and Cronbach's alpha measures 0.862. The reliability indicators (CR) of SRL, PKG, ATT, and GPI together exceeded 0.805, while Cronbach's alpha registered between 0.804 and 0.930. GPB config confirms good indicator quality: its loadings for outer factor are in an upper band (0.856–0.890) and AVE (0.760) surpass proposed thresholds, both suggesting consistent measurement and adequate convergent validity.

Reliability and validity of all constructs, AI-personalized learning (AI), self-regulated learning (SRL), perceived knowledge gain (PKG), attitude towards green purchasing (ATT), green purchase intention (GPI), and green purchasing behavior (GPB) achieved set standards [41]. Such control merits interpreting structural relationships cautiously while being careful with contextual meaning across contexts. Table 4 presents variance inflation factors for all the measures; in line with best practice, this safeguards against multicollinearity distortions with the use of extremely correlated predictors [41]. All the measures were below the standard threshold, indicating no notable multicollinearity problems [41], [42]. Together, these indicators of assurance lend credence to policy-relevant conclusions about the fit between platform-mediated learning and sustainability-focused outcomes under diverse conditions of connectivity and data governance.

Table 4: Variance inflation factor (VIF) of the model

Items	VIF
AI1	1.847
AI2	2.603
AI3	2.564
ATT1	2.691
ATT2	1.756
ATT3	2.385
GPB1	2.110
GPB2	2.465
GPB3	2.984
GPB4	2.923
GPI1	3.612
GPI2	3.538
GPI3	3.637

Items	VIF
GPI4	3.909
PKG1	2.326
PKG2	3.612
PKG3	2.639
PKG4	3.082
SRL1	1.744
SRL2	1.792
SRL3	1.679

All the variance measures of the inflation model were under five, indicating minor multicollinearity. Low risk (around 1.68–2.98) was evident for AI, SRL, ATT, and GPB indicators, while for PKG and GPI indicators, risk was moderately high (around 2.33–3.91), which ensured indicator uniqueness. These tests support the model's suitability for SEM.

Model fit in Table 5 was assessed for both saturated and estimated solutions using SRMR, d_ ULS, and d_ G, with χ^2 and NFI as adjuncts [41]. Acceptable fit is reflected in low SRMR (typically under .08), limited divergence between d_ ULS and d_ G, non-significant or near-non-significant χ^2 given its sample-size sensitivity, and NFI values trending toward one (rule-of-thumb $\geq .80$). Considered jointly, these indices justify proceeding to the structural model. The clean measurement and acceptable global fit also strengthen confidence in policy-relevant comparisons across contexts that differ in connectivity and data-governance conditions.

Table 5: model fit indices for both the saturated model and the estimated model

Model Fit	Saturated model	Estimated model
SRMR	0.069	0.078
d_ ULS	1.089	1.392
d_ G	0.623	0.658
Chi-square	2727.340	2738.065
NFI	0.810	0.810

We evaluated global fit for the structural and saturated models in PLS-SEM using recommended indices [41]. The SRMR, which summarizes the average discrepancy between observed and model-implied correlations, met conventional standards for both solutions: 0.079 for the estimated model and 0.069 for the saturated model, each ≤ 0.08 , indicating acceptable fit. The d_ ULS difference of 1.392 was also within acceptable ranges when coupled with d_ G, and there was no material difference between the two. These indices taken together imply that the model is adequate for mapping the structural relationships into it. Such measurement assurance, for its part, lends validity to policy-relevant inferences about how platform-enabled learning is mapped into sustainability-oriented outputs across environments with different levels of connectivity and data governance arrangements.

The d_ G index, a geometric difference between observed and model-implied matrices, was used as another fit measure; values close to one are acceptable. In our model, the d_ G = 0.658 for the estimated model and d_ G = 0.623 for the saturated model both indicate a good fit. The NFI, for comparison to the reference model and the baseline, was 0.810, which is acceptable for complex PLS-SEM applications and close to the threshold desirable value [41]. Combined with SRMR and d_ ULS, these metrics indicate sufficient global fit by modern standards [41], in favor of the interpretation of the structural relationships. The adequacy of fit supports the validity of policy-oriented inferences about how platform-governed, AI-facilitated learning converts into sustainability-oriented outcomes across environments differing in connectivity and data governance frameworks.

4.1. Structural model

After establishing measurement quality, we evaluated the structural model and tested specification with Confirmatory Tetrad Analysis (CTA) alongside mediation analyses of the path coefficients. CTA is a PLS-SEM diagnostic that helps distinguish reflective from formative specifications by examining tetrad (co)variances (Sarstedt et al., 2020). As reported in Table 6, GPI shows a non-significant tetrad frequency ($p = 0.652$) in the retained solution, consistent with a reflective structure, whereas an alternative frequency is significant ($p < 0.001$). In contrast, most tetrad frequencies for PKG and GPB are significant ($p < 0.05$), signaling potential formative tendencies. Guided by theory and prior measurement practice, we retain GPI and PKG as reflective, in TPB and learning-outcome contexts, they are modeled as latent traits manifested by their indicators, while GPB is treated as formative given its behavioral, potentially composite nature [41].

The reflective decisions are further supported by strong outer loadings (> 0.80), high composite reliability (> 0.90), $AVE > 0.50$, and $VIF < 5$, indicating internally consistent indicators, adequate convergence, and no problematic multicollinearity. Substantively, the three GPI items (willingness and future-oriented readiness to buy green) behave as parallel reflections of a single intention construct, and the PKG items capture a common latent perception of learning gains from AI-personalized study rather than distinct causal facets. Together, CTA evidence and classical criteria justify the reflective modeling of PKG and GPI, with GPB treated as formative, aligning the measurement with theory and supporting policy-relevant structural inferences about how platform-enabled learning translates into sustainability-oriented behavior.

Table 6. Confirmatory tetrad analysis (CTA)

Const ruct	Items	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	CI low	CI up
GPB	1: GPB1, GPB2, GPB3, GPB4	0.012	0.012	0.005	2.671	0.008	0.005	0.020
	2: GPB1, GPB2, GPB4, GPB3	0.019	0.019	0.005	4.155	0.000	0.012	0.027
GPI	1: GPI1, GPI2, GPI3, GPI4	-0.003	-0.003	0.006	0.451	0.652	-0.013	0.007
	2: GPI1, GPI2, GPI4, GPI3	0.021	0.021	0.004	5.293	0.000	0.015	0.028
PKG	1: PKG1, PKG2, PKG3, PKG4	0.017	0.017	0.006	2.904	0.004	0.007	0.026
	2: PKG1, PKG2, PKG4, PKG3	0.016	0.016	0.006	2.700	0.007	0.006	0.025

The figure below displays relationships between AI personalized learning (AI), students' self-regulated learning (SRL), perceived knowledge gain (PKG), attitude toward performing green purchasing (ATT), green purchase intention (GPI), and green purchasing behavior (GPB) through PLS-SEM structural modeling. The relationships between variables become visible through path coefficients as well as R^2 values, and their significance is indicated by p-values in brackets.

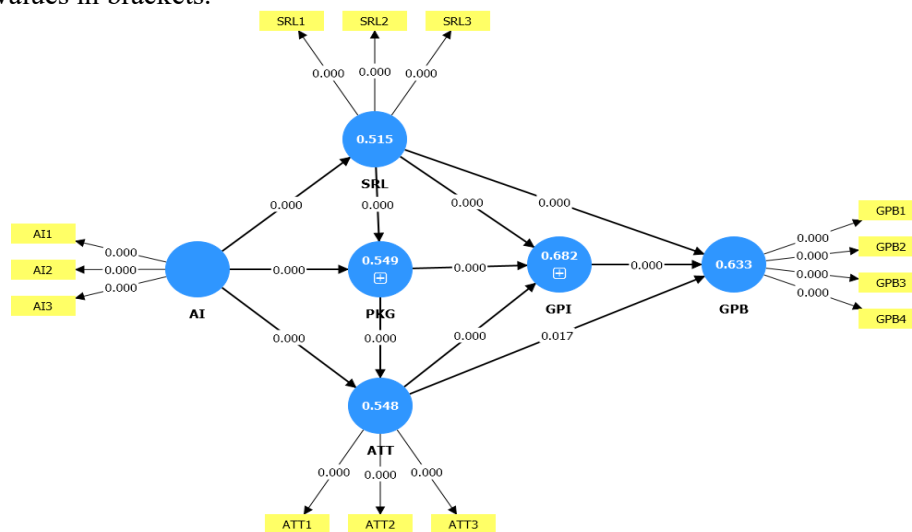


Figure 3: Structural (AI personalized learning (AI), students' self-regulated learning (SRL), perceived knowledge gain (PKG), attitude towards performing green purchasing (ATT), green purchase intention (GPI), green purchasing behavior (GPB)) Model

The structural model depicted in Figure 3 indicates the directional relationships among AI personalized learning (AI), students' self-regulated learning (SRL), perceived knowledge gain (PKG), attitude towards performing green purchasing (ATT), green purchase intention (GPI), and green purchasing behavior (GPB). The relationships are interpreted using the path coefficients with the R^2 statistics and p-values, which indicate the size and significance of the relationships.

Table 7 exhibits PLS-SEM results, which show that AI personalized learning (AI), students' self-regulated learning (SRL), perceived knowledge gain (PKG), attitude towards performing green purchasing (ATT), green purchase intention (GPI), and green purchasing behavior (GPB). Both direct and indirect influences from AI personalized learning reach green purchasing behavior (GPB) because SRL, PKG, ATT, and GPI work as a mediating effect.

Table 7: Results of the structural model

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	F ²	R ²
H1	AI -> SRL	0.718	0.718	0.017	42.032	0.000	1.062	0.515
H2	SRL -> PKG	0.610	0.611	0.037	16.317	0.000	0.401	0.549
	PKG -> ATT	0.207	0.206	0.031	6.716	0.000	0.060	0.548
H4	ATT -> GPI	0.602	0.602	0.032	18.716	0.000	0.577	0.682
H5	GPI -> GPB	0.221	0.221	0.042	5.304	0.000	0.044	0.633

The structural model results using PLS-SEM showed that all five hypotheses H1-H5 were supported at a high point of significance ($p < 0.001$). These indicate not only strong support for the causal pathway proposed in the study's theoretical model linking AI-powered personalized learning to sustainable consumer behavior outcomes, but also for the mediating role of educational and psychological variables.

(H1): The results indicated an strong impact of AI-powered personal learning on self-regulated learning (SRL) ($\beta = 0.718$, $T = 42.032$), and corroborated what the SRL literature suggested, that smart learning environments provide students with tools and strategies for regulating their learning, and personalization and immediate feedback were contributing factors to self-planning and monitoring [2], [10]. (H2): The relationship between SRL and perceived knowledge gain (PKG) was positively and statistically significantly related ($\beta = 0.610$, $T = 16.317$), which means some students were more self-regulated and thus felt they gained more knowledge. Literature supports this relationship, as self-regulatory strategies facilitate learners to feel cognitive improvement [1].

(H3): PKG had a positive effect on attitude toward performing green purchasing (ATT) ($\beta = 0.207$, $T = 6.716$), providing evidence that education (specifically around sustainability) can help build positive attitudes towards environmental behavior. In support of this, the TPB model acknowledges knowledge as a facilitating factor of attitudes [7], [21]. (H4): Green purchasing attitude significantly shaped green purchasing intention (GPI) ($\beta = 0.602$, $T = 18.716$), reinforcing the traditional argument of the Theory of Planned Behavior [6], which contends that attitude is one of the strongest predictors of behavioral intention, and consistent with meta-analytic reviews [8]. (H5): Based on the results, green purchasing intention (GPI) was a strong predictor of actual green purchasing behavior (GPB) ($\beta = 0.221$, $T = 5.304$). Thus, supporting the validity of the latter path in the TPB model, and emphasizing that increasing GPI is an important step in motivating actual environmental behaviour, even though the intention-behavior gap is acknowledged [30].

In terms of explanatory power, the model accounts for substantial variance at each stage: SRL ($R^2 = 0.515$), PKG ($R^2 = 0.549$), ATT ($R^2 = 0.548$), GPI ($R^2 = 0.682$), and GPB ($R^2 = 0.633$). These values translate to the mediators as a whole, carrying important information from learning to behavior. The largest impact is on the AI-personalized learning-to-self-regulated learning path, indicating personalization is the source of the cascade. The remaining relationships are small to moderate in size but are in fact significant given their cumulative effect

as the path continues on to actual green purchasing. Taken together, the trend indicates that policies are creating uniform access, affordable connectivity, and safe data governance. These antecedents of successful personalization can attain measurable gains along the entire learning-to-marketplace-action continuum.

These findings are aligned with the conceptual framework of this study: AI-supported learning platforms nurture self-regulated learning, strengthening cognitive awareness among learners about what they have learned, which translates into more favorable green purchase attitudes to influence intentions and, in turn, behavior. The integration of the theory of planned behavior, the theory of self-regulated learning, and the service-dominant logic thus captures a coherent explanation of innovation learning being enacted in transformative sustainable behavior.

4.2. Analysis of differences between countries

We used PLS-SEM with multi-group analysis to compare the path coefficients of Jordan's and Palestine's two cohorts and determine whether their structural relations differ significantly. The non-parametric permutation test was employed to accomplish this objective, a test based on randomly reallocating the data between the two groups many times (replications in this study). The model is then successively re-estimated, and the differences between the path coefficients obtained are calculated [41].

Table 8. PLS-MGA Comparison

Path	Diff	P-Perm
AI -> SRL	0.0107	0.7960
SRL -> PKG	0.0224	0.5100
PKG -> ATT	0.0055	0.9260
ATT -> GPI	0.0327	0.4120
GPI -> GPB	0.0107	0.8020

The results of Table 8 indicated that there were no statistically significant differences at the 5% level between the two research groups (Jordan and Palestine) in all paths of the proposed model. The permutation test p-value for all paths was greater than 5%. Accordingly, these results indicate that the strength and direction of the relationship between the variables in the model do not differ significantly between the two groups, suggesting homogeneity of sample behavior in both Jordan and Palestine regarding this model.

5. Discussion

The findings align closely with the theorized TPB–SRL–S-D logic pathway linking AI-personalized learning to green purchasing outcomes. Interpreted with due caution for a cross-sectional design, the pattern of statistically robust associations positions AI-personalized learning as an educational context that is consistent with stronger self-regulated learning (SRL), heightened perceived knowledge gain (PKG), more favorable pro-environmental attitudes, higher green purchase intentions (GPI), and, ultimately, greater self-reported green purchasing behavior (GPB).

First, perceived AI-personalized learning showed a large positive association with SRL ($\beta \approx 0.72$), aligning with SRL accounts that emphasize feedback-rich, learner-centered environments for planning, monitoring, and regulation, and with evidence from intelligent tutoring showing that contingent personalization strengthens metacognitive strategy use [1], [2], [10]. Read through S-D Logic, this underscores the learner as a co-producer of knowledge in a service system [9]. Second, SRL PKG was positive and sizeable ($\beta \approx 0.61$), consistent with findings that goal setting, strategic study, and self-monitoring yield greater perceived gains [14], [18] and extend this link to an AI-assisted, sustainability-relevant context [17].

Third, PKG \rightarrow Attitude toward green purchasing was positive though modest ($\beta \approx 0.21$): knowledge often functions as a distal antecedent shaping evaluative appraisals in pro-environmental domains [7] [21]. In TPB terms [6], learning-induced knowledge contributes upstream to more favorable attitudes while coexisting with value and social influences [25]. Fourth, Attitude \rightarrow GPI was strong ($\beta \approx 0.60$), mirroring TPB's core proposition and meta-analytic evidence that attitude is the dominant proximal driver of intention in green consumption [8], [26], [27].

Finally, GPI \rightarrow GPB was positive but modest ($\beta \approx 0.22$), consistent with the intention-behavior gap [30]. That intentions still translate into behavior, albeit imperfectly [31], highlights the role of situational enablers, availability, affordability, and convenience in converting intention into action [33]. These enablers are policy addressable via connectivity quality, fair pricing, and trustworthy data governance that sustain engagement and follow-through on platform-mediated learning.

In total, the cumulative pathway has: AI-personalized learning \rightarrow SRL \rightarrow PKG \rightarrow Attitude \rightarrow Intention \rightarrow Behavior. Explanatory power is large across endogenous measures, SRL ($R^2 \approx 0.52$), PKG (≈ 0.55), Attitude (≈ 0.55), Intention (≈ 0.68), and Behavior (≈ 0.63), such that the pathway explains a very large proportion of psychological and behavioral variance. Multi-group analysis shows largely similar patterns in Palestine and Jordan, showing preliminary cross-context validation in a Middle Eastern higher-education setting. Theoretically, the results validate TPB's attitudinal core but extend it with a proximal cognitive antecedent, perceived knowledge gain produced in an educational service interaction, and they identify the adaptive resilience of SRL under personalization, demystifying adaptive scaffolding's expression in perceived learning. READ under Service-Dominant Logic, the discoveries cross boundaries: knowledge coproduced in a learning service serves as an operant resource students later mobilize in consumption, illustrating how value co-creation in one context can impinge on value-laden behavior in another. The pathway's resilience identifies policy-actionable levers, access, affordability, data protection, and transparent personalization as determinants of whether platform-based learning cascades reliably to greener market alternatives in different connectivity and governance contexts.

In practice, AI-personalized systems can accomplish more than grade lifting; they can assist in shaping mindsets for sustainability. Personalized courses in combination with strategies to facilitate self-regulated learning, goal setting, reflective questions, and adaptive hints will have a better chance of engaging perceived knowledge more extensively and, ultimately, facilitate positive attitudes and intentions towards green shopping. Because intention is not action, last-mile facilitators matter: convenient access to trusted green options, affordability interventions, campus choice-architecture nudges, and implementation intention cues can help translate resolve into habitual action. The authority of such levers relies on governance: lasting effect relies on safe and accessible connections, trusted practices in data, and open rules for personalization that together enable participation and follow-through.

The structure is amenable to associational, but not causal, inferences; given evidence of post-learning experience behavior, stronger inferences would be obtained from longitudinal or experiment-based studies. Furthermore, some aspects of the theory of planned behavior, i.e., subjective norms and perceived control, and other contextual moderators have been excluded from the present specification on purpose. These must be incorporated in subsequent studies and tested for the model's robustness to longer horizons and in mixed telecom and data governance settings.

As a whole, the evidence sets out a plausible path of learning individualization to consumption for sustainability: intensified self-regulated learning is associated with increased perceived knowledge underpinning improved attitude, increased intention, and, less than optimally but significantly, action. This bridging from classroom to marketplace offers theoretical understanding and process guidance for educators, EdTech designers, and policymakers keen to bridge learning innovation and pro-environmental action. Its validity is regime contingent: equitable connectivity, secure practice of data, and transparent open personalization rules enhance the scaling of platform-enabled learning into greener alternatives.

6. Conclusion

6.1. Theoretical contributions

The research creates a synthesized theory of how AI-personalized learning can affect sustainable consumption by aligning the Theory of Planned Behavior, the theory of self-regulated learning, and Service-Dominant Logic, and exploring their combined effect in the context of a Middle Eastern university. Given the cross-sectional design, the convergent pattern of associations both confirms the fundamental implications of these traditions and lends them substance. These show how a platform-mediated learning experience can embed dispositions that, in turn, inform subsequent market decisions, in spaces defined by connectivity, data practices, and algorithmic transparency.

According to the Theory of Planned Behavior, our results align with the existing view that favorable attitudes towards green consumption yield stronger intentions and eventually higher probabilities of performance [8], [26], [27]. Within this university setting, the attitudinal route is very salient. Beyond corroborating TPB, we extend it by treating perceived knowledge gain as an explicit cognitive antecedent of attitude, an operationalization of a background factor typically left outside the core path [6]. Consistent with prior work, gains in sustainability-relevant knowledge align with more favorable appraisals of green consumption [7], [21]. Framed this way, education-driven cognitive change becomes a practical upstream lever for shifting the attitudinal determinant of intention in sustainability contexts.

From a self-regulated learning standpoint, the evidence shows that regulation is malleable and responsive to design. AI-personalized experiences align with accounts that emphasize feedback-rich, learner-centered supports for goal setting, monitoring, and strategic adjustment [1], [2]. In turn, strengthened regulation is accompanied by stronger perceptions of learning, clarifying how improved management of study processes is reflected in cognitive self-appraisals [14], [17], [18]. Taken together, these links, personalization, regulation, and perceived gain, place regulation upstream of attitudinal change and connect learning-science constructs to behavior-change models: personalization fosters self-regulation; regulated learners extract more value from the same content; perceived gains then inform attitudes toward sustainable consumption. This reading is consistent with research on intelligent and adaptive systems, where contingent feedback, calibrated help-seeking, and student-centered design cultivate metacognitive strategy use and self-regulatory competence [10].

Framing the AI-personalized platform as a service system clarifies how value co-creation in education can travel into consumption. Through their interactions, students and the platform generate operant resources, notably self-regulatory capabilities and knowledge, that learners later bring to decisions about green products. This resource-enhancement view accords with Service-Dominant Logic, which treats value as co-created in use and knowledge as a pivotal operant resource [9]. Our pathway renders that logic concrete: the value co-created in the learning service (SRL, PKG) is subsequently mobilized in another domain (attitudes, intentions, behavior), illustrating the portability and integration of resources across contexts.

No single framework anticipates the full sequence from personalization to behavior. By joining the Theory of Planned Behavior, self-regulated learning theory, and Service-Dominant Logic, we show, first, how designable features of an educational service foster learner agency; second, how that agency is expressed cognitively as perceived knowledge; and third, how cognition feeds TPB's attitudinal core to shape intention and, to a lesser extent, behavior. Evidence of explanatory coherence across the endogenous constructs suggests that this joined-up account captures variance typically dispersed across separate literatures. The comparability of patterns across Jordan and Palestine further indicates that these mechanisms are not tied to a single national setting, offering preliminary cross-context support for TPB's attitudinal primacy and for the generalizability of SRL in AI-enabled courses [26], [35].

Boundary conditions and agenda. These advances should be read with guardrails. The design supports associational rather than causal claims; when we speak of pathways, we refer to statistically estimated links aligned with theory, not experimentally identified effects. Salient TPB elements, subjective norms, perceived behavioral control, and other context moderators were intentionally excluded from this specification; future

studies must incorporate these factors and examine moderators such as past behavior and habit [32]. The reliably observed intention-behavior gap also needs caution: planning aids and facilitating contexts typically help intentions to be translated into action [31]. In the future, studies must investigate how differences in access, affordability, data protection, and transparency of personalization influence these linkages between environments.

This study links educational psychology and sustainable marketing via the illustration that AI-driven personalization is consistent with a theory-guided chain: it fosters self-regulated learning, increases perceived knowledge, and channels these advantages through the attitudinal mechanism of the Theory of Planned Behavior to intention and behavior. Treating knowledge as a co-created operant resource connects classroom innovation with marketplace implications, offering a portable template for explaining how educational service innovations can foster pro-environmental orientations [7], [8], [9], [10]. Above all, the strength and reach of this chain depend on governance: good connectivity, sound data practices, and ethical personalization are likely to strengthen the translation of learning on platforms into more sustainable decisions at scale.

6.2. Practical contributions

The findings chart out an actionable plan of action for universities, platform designers, and policymakers with a focus on fostering sustainability. Well-crafted AI-personalized learning has the potential to enhance performance but, even more importantly, promote self-regulated learning, increase perceived knowledge, and, through the attitudinal process that is the crux of the theory of planned behavior, steer students towards pro-environmental intention and action. With causal claims in mind, the operational lesson is to design learning environments that not only deliver content but also deepen learners' capacity to master learning and to judge sustainability choices, under conditions of governance that provide access, credible data practice, and open personalization.

At the platform and policy governance levels, the model provides a governable trajectory from platform norms and digital infrastructure to sustainability outcomes. AI-personalized learning constitutes a data-intensive platform that's embedded in algorithmic accountability norms, privacy regimes, and connectivity markets. By showing how personalization boosts self-regulation and perceived knowledge, transferable cognitive capital that facilitates pro-environmental intentions and attitudes, we set the stage for where telecommunications policy on access, affordability, and reliability, and platform governance on data protection, transparency, and auditability can turn on or dial down the social payoffs of personalization.

At the course and program level, the incorporation of adaptive, feedback-rich modules within sustainability-related curricula can promote self-regulated learning and, in turn, perceived knowledge. In practice, educators and platform providers are recommended to incorporate SRL-supportive features, goal-setting apparatuses, timely formative feedback, reflective prompts, and hints that progressively fade to promote autonomous problem solving [1], [10]. When students recognize actual learning improvements, such as cognitive self-evaluation becomes a lever for the development of attitudes toward green consumption, an educational entry point to consumer spheres [7], [21].

Given that attitude is the strongest motivator for intention in this case, initiatives that seek pro-environmental conduct need to go beyond offering information in order to create favorable appraisals [6], [8], [26], [27]. In practice, this means making sustainability real at an individual level: project-based activity based on local issues, reflective practice that connects decisions to values among students, and the logical use of role models or social proof to maximize support [25], [28]. The objective of operations is to couple the cognitive edge of AI-personalized learning with pedagogies that win hearts as well as minds, so that intentions would be derived from genuine attitudinal commitment.

Policy, three levers must be the priority. Getting in and being able to pay for it is first: improved broadband and pupil data for poorer communities increases the likelihood that personalization delivers the self-regulation and learning benefits underlying greener choices. Second is protecting data with real user control: layered consent,

minimization, portability, and effective opt-out build trust and enable the attitudinal pathway. Finally, algorithmic auditability and transparency, open reveals of profiling inputs and adaptation logic in simple terms, and routine independent audits help align provider incentives with public interests, subverting optimization for raw participation and redirecting it to learning-to-sustainability objectives.

Closing the intention-behavior gap includes education with the aid of enablers that make action easy. Campuses can introduce campus "green nudges" and supportive choice architectures, convenient access to proven sustainable alternatives, festivals where vetted alternatives are showcased, and reward schemes for green expenditures, thereby removing situational frictions and enabling intentions to be translated into action [30], [31]. At the same time, requesting students to form implementation intentions, elaborate plans of when, where, and how, can turn motivation into automatic action, and low-commitment devices can routinize new habits in a facilitating campus environment [34]. At the policy-making level, ministries and regulators can require privacy-preserving telemetry and pre-registered outcome measures in public procurement of AI-learning platforms, and incentivize staggered roll-outs and platform-side A/B tests under open data-protection assurances. Such designs allow for realistic causal assessment of whether affordability policies, consent redesign, or transparency provisions do indeed fortify the link from learning to more sustainable consumption.

Institutionally and policymaking-wise, it seems to find synergies between digital transformation and sustainability in Jordan, Palestine, and elsewhere, where e-learning and AI systems are on the rise. Enabling innovation and adoption of AI-tailored learning, especially when integrated with sustainability education subject matter, can impact students who are both tech-savvy and inclined toward ethical consumption, enabling a virtuous cycle among education and cleaner markets following Education for Sustainable Development. Such advantages exist due to the government: equitable connectivity, actual data security, and transparent personalization are the conditions under which the positives of the platforms are maximized.

To EdTech developers, the intimate relationship between self-regulated learning and personalization means that learning platforms need to work as learning skills trainers rather than content pipes. Clear goal dashboards, meaningful progress suggestions, reflective self-monitoring triggers, and adaptive assistance that gradually recedes with growing proficiency can inculcate enduring self-regulatory habits [10]. These are the gateway through which knowledge gain is translated to attitudes and, later on, implemented intentions [8], [21]. Generally, integrating AI-personalized learning with SRL-centered design, attitude-centered pedagogy, enactment facilitators, and supportive school policy offers an integrated end-to-end journey from doing to learning in sustainability.

6.3. Limitations and Future Research Directions

These findings are to be viewed in context. While the benefits of the model are proven, generalization beyond the present conditions has to be approached cautiously. Participants were students at a university, often receptive to online education and, at times, more environmentally aware than other groups, so effects may differ among older or less highly educated consumers. Self-report dependence heightens the threat of common-method bias and social desirability; timing and assurances of anonymity were useful, but such hurdles are inherent to field surveys. The model is deliberately parsimonious, and true green purchasing is also driven by prices, peer pressure, and infrastructure that we could not fully capture. Follow-up research would extend the model to incorporate other components of the theory of planned behavior, testing moderators such as income, gender, and past behavior, and other cultures in order to control for variation in context. Graduation persistence could be measured with longitudinal designs, and experimental or quasi-experimental designs would improve causal inference. We will also need to investigate how access, affordability, data protection, and transparency of algorithms translate these relations in various contexts. We view this as a chance for interdisciplinary cooperation between teachers, psychologists, sustainability researchers, and platform developers at the intersection of learning innovation and environmental participation.

In short, this study puts AI-adaptive learning in dialogue with behavior-change theory, showing how adaptive technologies combined with self-regulated pedagogies build knowledge and learning agency that translate to

pro-environmental action, intention, and behavior. The contribution is practical and conceptual: it sheds light on a potential trajectory from platform-based education to sustainable consumption and specifies how educators and designers can orchestrate long-term self-regulatory habits supporting this trajectory.

Evidence from Palestine and Jordan illustrates how learning-to-living can become a reality in development environments and under what conditions of governance it occurs at scale. The results show that there is a policy-addressable pathway: if access is low-cost and reliable, if data are protected with real user agency, and if personalization is explainable and auditable, social returns to AI-pushed learning are likely to materialize in the market. As institutions and governments seek out trusted solutions to environmental issues, an accessible lever awaits: classrooms that prepare students with autonomous, individual learning leading to more sustainable decisions.

We recommend a bundled strategy of three aligned elements. Infrastructure: target support for connectivity at those groups of students most likely to benefit from AI-personalized learning. Governance: adopt standard, layered transparency deliverables that describe the data capture and adaptation logic in plain language. Incentives: use outcome-based contracts that reward documented increases in self-regulated learning and perceived knowledge over plain usage. Together, these actions treat personalization as a governable platform technology whose social payback is greatest when telecommunications and data-policy tools are integrated.

Conflict of interest

The authors declare that they have no conflict of interest.

Author contributions

Khaled Alshaketheep: Conceptualization, methodology, Writing, review & editing. Hind Al-Ahmed: Conceptualization, investigation, visualization. Omar Zraqat: Methodology, formal analysis, validation. Ahmad Shajrawi: Project administration, resources, Data curation, writing - original draft.

Ethical Statement

This research was conducted in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments or analogous ethical standards. All participants in the quantitative surveys provided informed consent, and their privacy and confidentiality were strictly maintained. Ethical approval was obtained from the appropriate ethics review board prior to the commencement of the study.

Data availability statement

In accordance with Jordanian data privacy regulations and the Hashemite University Economic and Management Sciences Research Ethics Committee's data access restrictions, the dataset used in this study is not publicly available. However, the corresponding author can provide the relevant data upon reasonable request, in compliance with the applicable legal and ethical guidelines.

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