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Digital Literacy and Sustainable Shopping through AI Assistants

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ABSTRACT: Digital literacy may influence how consumers evaluate information and make sustainability-related decisions with conversational AI assistants. This paper examined the associations of technical, cognitive and socio-emotional literacy with environmental buying, environmental avoidance, social avoidance and actual premium payment, and assessed decision confidence as an intervening variable. The numerical analysis used 500 generated records, with outcome-specific usable samples ranging from 479 to 487. The reported analysis applied multiple regression with heteroskedasticity-consistent inference and resampling-based indirect-effect intervals. Technical literacy was positively associated with decision confidence ($B = 0.281$, $p < .001$); the cognitive and socio-emotional coefficients were not statistically significant. Decision confidence was positively associated with all four outcomes after adjustment for the literacy dimensions and controls, with coefficients ranging from 0.226 to 0.264 and Holm-adjusted p values below .001. Technical-literacy indirect effects ranged from 0.065 to 0.076, and all four multiplicity-adjusted intervals excluded zero. Corresponding indirect effects for cognitive and socio-emotional literacy did not meet that criterion. Outcome-model R^2 values ranged from .157 to .170. The findings illustrated a coherent distinction between information-evaluation skills, operational skills and confidence, while preserving the mixed component-level results. They provide an analysis framework and questionnaire for empirical validation; they do not establish population effects or causal mediation.

1 INTRODUCTION

Conversational AI assistants increasingly mediate product search, comparison and evaluation. Their ability to summarize alternatives can reduce the effort required to process product information, but the usefulness of that information depends on consumers' ability to formulate questions, evaluate claims and retain control of their decisions. Research on interactive decision aids and AI-enabled customer experience suggests that assistance can alter both the information environment and the consumer's experience of choice (Häubl & Trifts, 2000; Puntoni et al., 2021). The adoption of an assistant, however, does not establish that its recommendations are accurate, ethically appropriate or environmentally preferable.

Sustainable shopping is particularly demanding because relevant product attributes are often difficult to verify. Environmental labels, packaging claims, labour conditions and price premiums require different forms of evidence. The gap between ethical intentions and purchasing behaviour means that favourable attitudes cannot substitute for behavioural measurement

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(Carrington et al., 2010; Joshi & Rahman, 2015; Young et al., 2010). Environmental buying, avoidance of environmental harm, avoidance of social harm and payment of a sustainability-related premium were therefore treated as separate outcomes rather than interchangeable indicators of one universal purchasing tendency.

Digital literacy is also multidimensional. Technical skills concern operating digital systems, cognitive skills concern assessing information, and socio-emotional skills concern responsible interaction and self-regulation. General digital-literacy scholarship provides a foundation for distinguishing these dimensions, while AI literacy introduces additional concerns about system capabilities and limitations (Long & Magerko, 2020; D. T. K. Ng et al., 2021; W. Ng, 2012; van Laar et al., 2017). Applying these ideas to shopping requires an explicit measurement map rather than assuming that experience with technology implies competence in evaluating sustainability claims.

Decision confidence offers a plausible link between these skills and behaviour. Consumer self-confidence and confidence in choosing can affect the experience and resolution of a purchase decision (Bearden et al., 2001; Heitmann et al., 2007). Yet confidence can accompany incorrect information, and reliance on automation depends partly on calibrated trust (Lee & See, 2004). The present paper therefore examined associations rather than treating confidence as proof of decision quality. Its contribution was an aligned framework connecting three literacy dimensions, a clearly defined confidence construct and four distinct outcomes. The reported numbers were generated for analytical illustration; a field study remains necessary to evaluate whether these relationships occur among consumers.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2 1 Digital literacy and sustainable shopping

Technical literacy enables a consumer to enter queries, refine a comparison and inspect linked evidence. Cognitive literacy supports comparisons across sources and differentiation of claims from substantiation. Socio-emotional literacy supports privacy awareness, respectful interaction and resistance to inappropriate pressure. The Internet Skills Scale offers related measurement foundations, but it does not validate the new shopping-specific items in this paper (van Deursen et al., 2016). Technology acceptance research explains why perceived usefulness and ease of use may shape engagement; those concepts were not treated as equivalent to literacy (Davis, 1989; Venkatesh et al., 2003).

Sustainable consumption research distinguishes underlying values, ethical intentions and reported behaviour. Green consumption values and ethical consumption measures informed the coverage of environmental and social outcomes (Haws et al., 2014; Sudbury-Riley & Kohlbacher, 2016). The SHIFT framework further emphasizes that sustainable choices depend on psychological and contextual conditions (White et al., 2019). Perceived value, knowledge and trust are relevant to green purchasing, while greenwashing may weaken trust and increase confusion (Chen & Chang, 2013; Delmas & Burbano, 2011; Roh et al., 2022). Greater literacy could improve scrutiny of these signals, but its association may differ across outcomes. The following broad hypothesis was therefore examined through separate component paths.

H1. Digital literacy was positively associated with sustainable shopping outcomes in AI-assisted shopping.

2 2 Digital literacy and decision confidence

Competent use of a decision aid may reduce uncertainty about how alternatives were compared. Technical competence may help users obtain a usable comparison; cognitive competence may support evidence evaluation; socio-emotional competence may help maintain agency. AI service research suggests that different capabilities perform different roles in customer tasks (Huang & Rust, 2018; Huang & Rust, 2021). Trust in AI also depends on characteristics of the system, user and context, rather than on one stable disposition (Glikson & Woolley, 2020). These arguments motivated testing each literacy dimension while recognizing that the numerical analysis cannot identify a causal change in confidence.

H2. Digital literacy was positively associated with decision confidence in AI-assisted shopping.

2 3 Decision confidence and purchasing outcomes

Confidence can help a consumer commit to a choice, including a decision to avoid a product. The theory of planned behaviour provides a broader account of intention and behaviour, but confidence in a current decision is distinct from perceived behavioural control (Ajzen, 1991). Trust and technology acceptance research also highlights the importance of beliefs about online systems (Gefen et al., 2003). Algorithm aversion, algorithm appreciation and task dependence indicate that consumers may react differently to automated advice (Castelo et al., 2019; Dietvorst et al., 2015; Logg et al., 2019). Chatbot disclosure and

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anthropomorphic perceptions can further affect responses to AI interactions (Epley et al., 2007; Luo et al., 2019). Confidence was accordingly examined as a measured predictor, without assuming that stronger confidence always improves sustainability.
H3. Decision confidence was positively associated with sustainable shopping outcomes after accounting for digital literacy.

2 4 Indirect associations through decision confidence

Literacy may be associated with shopping outcomes partly through confidence. Indirect-effect analysis evaluates the product of a literacy-to-confidence coefficient and a confidence-to-outcome coefficient. A significant total association is not a prerequisite for an indirect effect, and the indirect-effect distribution requires appropriate interval estimation (MacKinnon et al., 2004; Preacher & Hayes, 2008; Zhao et al., 2010). Nevertheless, an indirect statistical association does not itself establish mediation as a causal process. Cross-sectional mediation can be misleading when temporal processes are not correctly represented (Maxwell & Cole, 2007).
H4. Digital literacy had positive indirect associations with sustainable shopping outcomes through decision confidence.

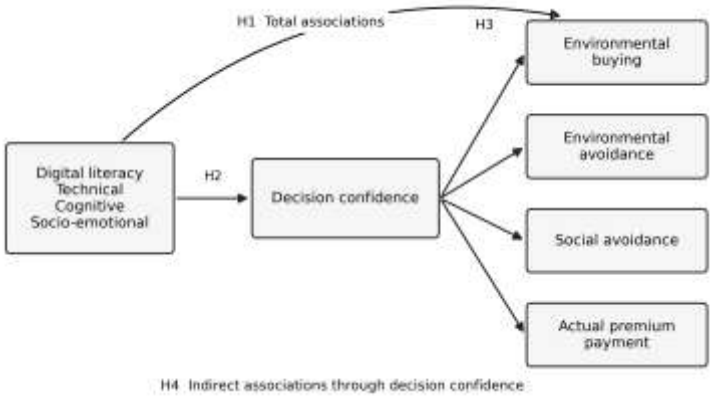


Figure 1: Conceptual framework linking literacy dimensions decision confidence and purchasing outcomes

3 RESEARCH METHODOLOGY

The study used an observational regression framework applied to 500 computer-generated records. The analysis distinguished technical literacy (DLT), cognitive literacy (DLC), socio-emotional literacy (DLS), consumer decision confidence (CDC), environmental buying (EB), environmental avoidance (EV), social avoidance (SB) and actual premium payment (PM). Each construct contained five items. Literacy and confidence used five-point agreement responses, while purchasing outcomes used five-point frequency responses with an additional not-applicable option for a lack of opportunity or inability to judge. Composite scores were defined as the mean of at least four valid items; not-applicable responses were excluded rather than coded as zero or as "never". Outcome-specific usable samples consequently ranged from 479 to 487, and complete-item samples used for reliability and sensitivity analyses were smaller. The questionnaire was adapted conceptually from the literature and was not presented as an independently validated instrument. The reported analysis used ordinary least squares with the three literacy dimensions entered together, categorical controls for income, online-shopping experience and AI-use frequency, and HC3 heteroskedasticity-consistent covariance estimates (MacKinnon & White, 1985). The confidence model assessed H2; models excluding and including confidence assessed total and conditional associations for H1 and H3. Joint literacy tests used Wald χ^2 statistics with three degrees of freedom. Holm adjustment was applied across the four joint H1 tests and separately across the four H3 confidence tests. Component H1 and H2 p values were nominal and were treated as exploratory. The reported indirect-effect procedure used 5,000 bootstrap resamples and outcome-specific matched cases; nominal 95% intervals and Bonferroni-adjusted 99.583% intervals were reported for the family of 12 indirect effects. Complete-item sensitivity analyses examined the confidence coefficient. All coefficients were unstandardized. The present reconstruction checked the arithmetic and alignment of the retained rounded summaries; the respondent-level workbook, bootstrap draws and original analysis code were unavailable, so the models were not independently re-estimated. Internal consistency was summarized with coefficient alpha, which establish validity (Cho, 2016; Cronbach, 1951; McNeish, 2018).

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Table 1: Construct definitions measurement map and hypothesis alignment

Code	Construct and focus	Items	Conceptual sources	Role
DLT	Operating and refining AI comparisons	Q11–15	W. Ng, 2012; van Deursen et al., 2016; Long & Magerko, 2020	H1 H2 H4
DLC	Evaluating relevance evidence and credibility	Q16–20	W. Ng, 2012; van Deursen et al., 2016; D. T. K. Ng et al., 2021	H1 H2 H4
DLS	Privacy interaction and decision autonomy	Q21–25	W. Ng, 2012; Long & Magerko, 2020	H1 H2 H4
CDC	Confidence in the current comparison decision	Q26–30	Bearden et al., 2001; Heitmann et al., 2007	H2 H3 H4
EB	Environmentally preferable purchases	Q31–35	Haws et al., 2014; Sudbury-Riley & Kohlbacher, 2016	H1 H3 H4
EV	Avoiding environmentally harmful products	Q36–40	Sudbury-Riley & Kohlbacher, 2016; White et al., 2019	H1 H3 H4
SB	Avoiding purchases associated with social harm	Q41–45	Sudbury-Riley & Kohlbacher, 2016	H1 H3 H4
PM	Reported actual sustainability-related price premiums	Q46–50	Young et al., 2010; White et al., 2019	H1 H3 H4

4 Results

4. 1 Profile of the generated records

The analysis contained 500 records. The largest age category was 35–44 years (22.4%). Income categories and AI-use frequency were distributed across all specified levels. Table 2 retained men and women as the two displayed gender categories, but these categories accounted for only 352 records. The remaining 148 records (29.6%) were outside the two displayed categories in the retained source summaries and were not redistributed.

Table 2: Demographic and usage profile

Variable	Category	n	% of 500
Age	18–24 years	90	18.0
	25–34 years	101	20.2
	35–44 years	112	22.4
	45–54 years	108	21.6
	55 years or older	89	17.8
Gender	Women	176	35.2
	Men	176	35.2
Monthly personal income	No personal income	89	17.8
	Below ₹15,000	81	16.2

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Variable	Category	n	% of 500
	₹15,000–₹29,999	87	17.4
	₹30,000–₹49,999	66	13.2
	₹50,000–₹74,999	94	18.8
	₹75,000 or more	83	16.6
AI shopping comparisons in past 3 months	1	101	20.2
	2–3	92	18.4
	4–6	100	20.0
	7–10	105	21.0
	More than 10	102	20.4

4. 2 Descriptive statistics and internal consistency

Technical and socio-emotional literacy recorded the highest literacy means (both M = 3.572), while decision confidence averaged 3.501. Environmental buying recorded the highest purchasing-outcome mean (M = 3.073), whereas actual premium payment recorded the lowest (M = 2.409). Standard deviations ranged from 0.610 to 0.705, describing the dispersion of scores within the respective constructs.

Cronbach's alpha ranged from .818 to .872, indicating internal consistency across the eight five-item scales in the reported analysis. Technical literacy recorded the highest alpha (.872), while social avoidance recorded the lowest (.818). These results supported.

Table 3: Descriptive statistics reliability

Construct	Score n	Mean	SD	Skewness	Items	Reliability n	Cronbach's α
Technical literacy (DLT)	500	3.572	0.695	−0.219	5	500	.872
Cognitive literacy (DLC)	500	3.276	0.692	−0.061	5	500	.858
Socio-emotional literacy (DLS)	500	3.572	0.667	−0.135	5	500	.846
Decision confidence (CDC)	500	3.501	0.705	−0.226	5	500	.867
Environmental buying (EB)	480	3.073	0.680	0.040	5	369	.865
Environmental avoidance (EV)	479	2.909	0.631	0.131	5	373	.823
Social avoidance (SB)	483	2.701	0.610	−0.012	5	376	.818
Actual premium payment (PM)	487	2.409	0.649	0.204	5	374	.848

4 3 Correlations

Technical literacy correlated with decision confidence at r = .331. Confidence correlations with purchasing outcomes ranged from .319 to .347. Correlations among literacy dimensions ranged from .411 to .575, supporting the need to distinguish bivariate relationships from coefficients estimated with the other dimensions included.

Table 4: Pearson correlation matrix

Variable pair	Pearson's r	Pairwise N	Approx. p (two-tailed)	Approx. 95% CI	Significance³
DLT–DLC	.575	500	< .001	[.513, .631]	Significant
DLT–DLS	.411	500	< .001	[.335, .481]	Significant
DLT–CDC	.331	500	< .001	[.251, .407]	Significant

DLT–EB	.244	480	< .001	[.158, .326]	Significant
DLT–EV	.250	479	< .001	[.164, .332]	Significant
DLT–SB	.251	483	< .001	[.165, .333]	Significant
DLT–PM	.247	487	< .001	[.162, .329]	Significant
DLC–DLS	.467	500	< .001	[.396, .533]	Significant
DLC–CDC	.256	500	< .001	[.172, .336]	Significant
DLC–EB	.286	480	< .001	[.202, .366]	Significant
DLC–EV	.286	479	< .001	[.202, .366]	Significant
DLC–SB	.215	483	< .001	[.128, .298]	Significant
DLC–PM	.217	487	< .001	[.131, .300]	Significant
DLS–CDC	.170	500	< .001	[.084, .254]	Significant
DLS–EB	.181	480	< .001	[.093, .266]	Significant
DLS–EV	.207	479	< .001	[.120, .291]	Significant
DLS–SB	.209	483	< .001	[.122, .293]	Significant
DLS–PM	.186	487	< .001	[.099, .270]	Significant
CDC–EB	.336	480	< .001	[.254, .413]	Significant
CDC–EV	.319	479	< .001	[.236, .397]	Significant
CDC–SB	.347	483	< .001	[.266, .423]	Significant
CDC–PM	.331	487	< .001	[.249, .408]	Significant
EB–EV	.145	459–479	.00146–.00184	[.054, .233]	Significant
EB–SB	.181	463–480	.00007–.00009	[.091, .268]	Significant
EB–PM	.185	467–480	.00005–.00006	[.096, .271]	Significant
EV–SB	.161	462–479	.00040–.00051	[.071, .249]	Significant
EV–PM	.187	466–479	.00004–.00005	[.098, .273]	Significant
SB–PM	.173	470–483	.00013–.00016	[.084, .259]	Significant

All correlations were positive and met the unadjusted .05 significance criterion under the stated calculations. Technical and cognitive literacy recorded the strongest association (r = .575). Decision confidence was positively associated with environmental buying (r = .336), environmental avoidance (r = .319), social avoidance (r = .347) and actual premium payment (r = .331). Its correlations with these outcomes were numerically larger than those of any individual literacy dimension. Associations among the purchasing outcomes were comparatively weak (r = .145–.187), indicating limited overlap in their scores.

4 4 Hypothesis testing

The tables report unstandardized coefficients (B), HC3 standard errors (SE), normal-approximation 95% confidence intervals (CI) and the specified multiplicity adjustments. Differences of approximately .001 between rounded coefficients and interval

calculations are compatible with reporting precision. Supported means that a positive component met its stated testing rule. Not supported means that it did not meet that rule; it does not prove the coefficient was exactly zero.

4 4 1 Total literacy associations

Table 5: Outcome model fit and joint literacy tests

Outcome	n	R^2 total	R^2 with CDC	Wald $\chi^2(3)$	H1 Holm p	H3 Holm p
EB	480	.103	.166	49.477	< .001	< .001
EV	479	.115	.170	48.849	< .001	< .001
SB	483	.090	.166	48.235	< .001	< .001
PM	487	.093	.157	36.608	< .001	< .001

The three literacy coefficients were jointly significant for every outcome (all Holm-adjusted $p < .001$). This joint result indicated evidence against an all-zero coefficient vector, rather than evidence that every literacy dimension was positive and significant. The total-association model R^2 values ranged from .090 to .115.

Table 6: Total literacy associations before including confidence

Outcome	Predictor	B	SE	95% CI	p
EB	DLT	0.114	0.056	[0.005, 0.224]	.040
EB	DLC	0.198	0.056	[0.089, 0.307]	< .001
EB	DLS	0.039	0.053	[−0.066, 0.143]	.470
EV	DLT	0.095	0.051	[−0.005, 0.194]	.062
EV	DLC	0.170	0.054	[0.064, 0.276]	.002
EV	DLS	0.076	0.048	[−0.017, 0.169]	.110
SB	DLT	0.152	0.048	[0.057, 0.247]	.002
SB	DLC	0.064	0.052	[−0.039, 0.167]	.220
SB	DLS	0.094	0.047	[0.003, 0.186]	.044
PM	DLT	0.158	0.053	[0.055, 0.261]	.003
PM	DLC	0.072	0.056	[−0.039, 0.183]	.202
PM	DLS	0.081	0.049	[−0.014, 0.177]	.094

At the nominal .05 level, technical literacy was positively associated with environmental buying, social avoidance and premium payment. Cognitive literacy was positively associated with environmental buying and environmental avoidance. Socio-emotional literacy was positively associated with social avoidance. Six of the 12 component tests met the nominal threshold. H1 consequently had mixed component evidence, even though all four joint tests were significant. These nominal component results were exploratory and were not promoted to familywise-adjusted findings.

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4 4 2 Literacy associations with decision confidence

Table 7: Regression of decision confidence on literacy dimensions

Predictor	B	HC3 SE	95% CI	p
DLT	0.281	0.054	[0.176, 0.387]	< .001
DLC	0.085	0.054	[−0.020, 0.190]	.114
DLS	0.016	0.053	[−0.088, 0.120]	.761

Technical literacy had a positive confidence coefficient (B = 0.281, p < .001). Cognitive literacy (p = .114) and socio-emotional literacy (p = .761) did not meet the nominal significance criterion. H2 was supported for technical literacy only. The model explained 12.7% of confidence variation; the significant joint test did not justify declaring all three component hypotheses supported.

4 4 3 Conditional associations with purchasing outcomes

Table 8: Outcome regressions including decision confidence

Outcome	Predictor	B	SE	95% CI	p
EB	DLT	0.041	0.054	[−0.064, 0.147]	.442
EB	DLC	0.171	0.054	[0.065, 0.278]	.002
EB	DLS	0.037	0.052	[−0.064, 0.139]	.469
EB	CDC	0.264	0.045	[0.175, 0.353]	< .001
EV	DLT	0.030	0.052	[−0.072, 0.132]	.563
EV	DLC	0.154	0.052	[0.052, 0.255]	.003
EV	DLS	0.074	0.045	[−0.015, 0.162]	.101
EV	CDC	0.226	0.043	[0.142, 0.310]	< .001
SB	DLT	0.085	0.048	[−0.009, 0.178]	.076
SB	DLC	0.046	0.050	[−0.052, 0.144]	.360
SB	DLS	0.089	0.045	[0.001, 0.176]	.047
SB	CDC	0.254	0.039	[0.177, 0.332]	< .001
PM	DLT	0.082	0.053	[−0.022, 0.187]	.122
PM	DLC	0.051	0.054	[−0.055, 0.157]	.347
PM	DLS	0.079	0.047	[−0.013, 0.171]	.093
PM	CDC	0.251	0.042	[0.169, 0.332]	< .001

Decision confidence was positively associated with environmental buying (B = 0.264), environmental avoidance (B = 0.226), social avoidance (B = 0.254) and actual premium payment (B = 0.251). All four Holm-adjusted tests were significant, supporting H3 across the four specified outcomes. Conditional cognitive-literacy coefficients remained significant for both environmental outcomes at nominal levels; the socio-emotional coefficient for social avoidance was also nominally significant. These coefficients did not establish causal direct effects. Including confidence increased R^2 to .157–.170.

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4 4 4 Indirect associations

Table 9: Bootstrap indirect effects through decision confidence

Outcome	Literacy	ab	Boot SE	95% CI	99.583% CI	Adjusted result
EB	DLT	0.073	0.019	[0.039, 0.112]	[0.024, 0.135]	Significant
EB	DLC	0.026	0.015	[−0.001, 0.059]	[−0.013, 0.076]	Not significant
EB	DLS	0.001	0.014	[−0.027, 0.029]	[−0.043, 0.044]	Not significant
EV	DLT	0.065	0.017	[0.035, 0.100]	[0.022, 0.121]	Significant
EV	DLC	0.016	0.012	[−0.008, 0.041]	[−0.019, 0.058]	Not significant
EV	DLS	0.002	0.012	[−0.022, 0.027]	[−0.034, 0.040]	Not significant
SB	DLT	0.068	0.016	[0.038, 0.101]	[0.026, 0.116]	Significant
SB	DLC	0.019	0.014	[−0.009, 0.048]	[−0.021, 0.061]	Not significant
SB	DLS	0.006	0.014	[−0.021, 0.034]	[−0.034, 0.050]	Not significant
PM	DLT	0.076	0.018	[0.043, 0.114]	[0.033, 0.134]	Significant
PM	DLC	0.021	0.014	[−0.005, 0.050]	[−0.020, 0.070]	Not significant
PM	DLS	0.002	0.013	[−0.024, 0.030]	[−0.036, 0.043]	Not significant

Technical-literacy indirect estimates were positive for all four outcomes, ranging from 0.065 to 0.076. Their adjusted intervals excluded zero. All eight adjusted intervals for cognitive and socio-emotional literacy included zero. Thus, H4 was supported for the four technical-literacy pathways and was not supported for the remaining pathways. The result was an indirect association within generated data, rather than confirmation that confidence caused a behavioural change.

4 5 Complete item sensitivity analysis

Table 10: Confidence coefficients among records with all five outcome items

Outcome	Complete-item n	CDC B	95% CI
EB	369	0.298	[0.195, 0.401]
EV	373	0.200	[0.106, 0.295]
SB	376	0.275	[0.187, 0.363]
PM	374	0.257	[0.162, 0.353]

The confidence coefficients remained positive in complete-item analyses, with intervals excluding zero for all four outcomes. Their magnitudes ranged from 0.200 to 0.298. This consistency supported the stability of the reported direction under the stricter scoring rule, but it did not establish that the not-applicable mechanism was ignorable or that the complete-item subset represented a population.

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4 6 Hypothesis decisions

Table 11: Broad hypothesis assessment

Hypothesis	Evidence	Overall assessment	Component decisions
H1	All four joint tests significant; component paths differ.	Mixed component evidence	6 supported; 6 not supported
H2	Technical path significant; other two not significant.	Mixed component evidence	1 supported; 2 not supported
H3	Four positive confidence coefficients; all Holm p < .001.	Supported across all four outcomes	4 supported; 0 not supported
H4	Four technical adjusted indirect intervals exclude zero.	Mixed component evidence	4 supported; 8 not supported

A broad hypothesis cannot be made fully accepted by relabelling nonsignificant components or altering coefficients. Binary decisions were therefore reported for each explicitly identified component in Table 12. H1 and H2 decisions used nominal p < .05, H3 used Holm-adjusted p < .05 and H4 used its adjusted interval. The component enumeration was an analytical breakdown of the original broad statements, not evidence of preregistration.

Table 12: Binary component decisions with the stated testing rule

Family	Path	B or ab	Evidence	Significance	Decision
H1	DLT → EB	0.114	p = .040	Significant	Supported
H1	DLC → EB	0.198	p < .001	Significant	Supported
H1	DLS → EB	0.039	p = .470	Not significant	Not supported
H1	DLT → EV	0.095	p = .062	Not significant	Not supported
H1	DLC → EV	0.170	p = .002	Significant	Supported
H1	DLS → EV	0.076	p = .110	Not significant	Not supported
H1	DLT → SB	0.152	p = .002	Significant	Supported
H1	DLC → SB	0.064	p = .220	Not significant	Not supported
H1	DLS → SB	0.094	p = .044	Significant	Supported
H1	DLT → PM	0.158	p = .003	Significant	Supported
H1	DLC → PM	0.072	p = .202	Not significant	Not supported
H1	DLS → PM	0.081	p = .094	Not significant	Not supported
H2	DLT → CDC	0.281	p < .001	Significant	Supported
H2	DLC → CDC	0.085	p = .114	Not significant	Not supported
H2	DLS → CDC	0.016	p = .761	Not significant	Not supported
H3	CDC → EB	0.264	Holm p < .001	Significant	Supported

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Family	Path	B or ab	Evidence	Significance	Decision
H3	CDC → EV	0.226	Holm p < .001	Significant	Supported
H3	CDC → SB	0.254	Holm p < .001	Significant	Supported
H3	CDC → PM	0.251	Holm p < .001	Significant	Supported
H4	DLT → CDC → EB	0.073	[0.024, 0.135]	Significant	Supported
H4	DLC → CDC → EB	0.026	[−0.013, 0.076]	Not significant	Not supported
H4	DLS → CDC → EB	0.001	[−0.043, 0.044]	Not significant	Not supported
H4	DLT → CDC → EV	0.065	[0.022, 0.121]	Significant	Supported
H4	DLC → CDC → EV	0.016	[−0.019, 0.058]	Not significant	Not supported
H4	DLS → CDC → EV	0.002	[−0.034, 0.040]	Not significant	Not supported
H4	DLT → CDC → SB	0.068	[0.026, 0.116]	Significant	Supported
H4	DLC → CDC → SB	0.019	[−0.021, 0.061]	Not significant	Not supported
H4	DLS → CDC → SB	0.006	[−0.034, 0.050]	Not significant	Not supported
H4	DLT → CDC → PM	0.076	[0.033, 0.134]	Significant	Supported
H4	DLC → CDC → PM	0.021	[−0.020, 0.070]	Not significant	Not supported
H4	DLS → CDC → PM	0.002	[−0.036, 0.043]	Not significant	Not supported

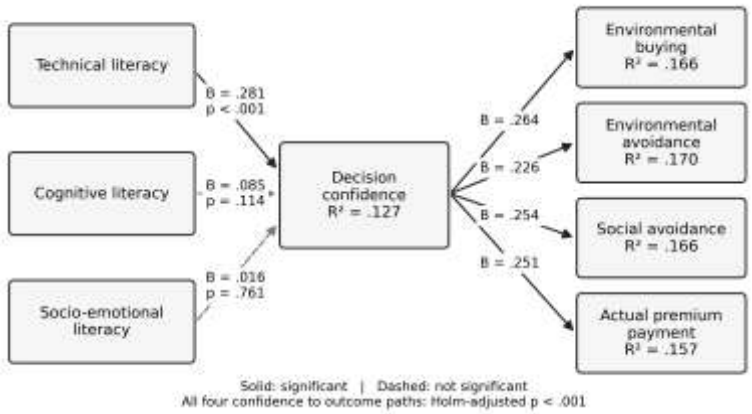


Figure 2; Regression associations between literacy decision confidence and purchasing outcomes

4 7 Main findings

1. Technical literacy was the only literacy dimension with a significant positive coefficient in the decision-confidence model.
2. All four confidence coefficients were positive and significant after adjustment across the four outcome tests.
3. Four technical-literacy indirect intervals excluded zero after adjustment across 12 indirect pathways.
4. Total and conditional literacy associations differed across outcomes, requiring component-level reporting rather than a universal acceptance claim.

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5. Complete-item sensitivity results retained positive confidence coefficients, while available R^2 values left most outcome variation unexplained.

5 DISCUSSION

The reported pattern separated two possible functions of literacy. Operational competence was associated with confidence and the indirect pathway, while cognitive literacy retained nominal conditional associations with environmental outcomes. The distinction is compatible with a consumer who can obtain a comparison but still needs to judge whether sustainability claims are credible. It also explains why a single digital-literacy average could obscure different component patterns. Because the data were generated, this compatibility illustrated how the framework could be interpreted rather than providing independent evidence for the theory.

The four confidence associations should not be read as evidence that confidence invariably improves consumer welfare. Confidence may reflect clearer preferences, but it may also reflect uncritical acceptance of fluent advice. Research on trust and reliance indicates that calibration matters (Glikson & Woolley, 2020; Lee & See, 2004). In the sustainability setting, meaningful improvement requires evidence about the decision's substance, including the credibility of environmental and labour claims. The premium-payment outcome was kept distinct from willingness to pay: a reported completed payment has different evidential requirements from a favourable intention.

The modest model R^2 values also matter. Income constraints, product availability, sustainability knowledge, trust, category differences and transaction opportunities may explain variation that the current specification did not capture. Statistical significance in a generated dataset cannot substitute for representative sampling, sound measurement or a credible identification strategy. Equally, nonsignificant paths should remain visible. Removing them would distort the pattern and encourage a stronger conclusion than the analysis supported.

5 1 Theoretical implications

The framework linked digital-literacy dimensions to a proximal decision state and to disaggregated behavioural domains. It avoided treating technology acceptance, trust, confidence and literacy as synonyms. It also distinguished total associations from conditional coefficients and indirect-effect products. Future empirical work could assess whether this structure is replicable and whether confidence adds explanatory value beyond prior preferences and product knowledge. Any claim of mediation would require defensible timing, confounding control and assumptions about the measured constructs.

5 2 Practical implications

The framework suggests that AI shopping support could combine usable comparison functions with verifiable evidence and opportunities for consumers to revisit their decisions. Sustainability claims should be traceable to sources, and the interface should identify missing information rather than treating fluent answers as assurance. These implications are design propositions for evaluation, not demonstrated effects of an intervention. Retailers and educators should assess decision quality and actual outcomes alongside confidence.

5 3 Limitations

1. Generated data limited external validity. The numerical results did not estimate effects among observed consumers and could not support population-level recommendations on their own.
2. Rounded-summary arithmetic was checked, but model estimation, bootstrap implementation and complete data processing could not be independently reproduced.
3. Measurement validity remained unestablished. Alpha did not confirm factor structure; no verified CFA, AVE, HTMT or independent validity evidence was available.
4. Indirect-effect estimates did not establish causation. Timing, common-source measurement, reverse direction and omitted variables remained relevant to any future field interpretation.
5. Outcome opportunity and sample composition constrained interpretation. Not-applicable responses produced different usable samples, exact pairwise correlation counts were unavailable and 148 records lay outside the two displayed gender categories.

5 4 Recommendations

1. Train users to formulate and refine product comparisons, then evaluate whether operational skill improvements translate into better verified choices.
2. Attach traceable evidence to environmental and labour claims, including the source, scope and date of certifications when available.
3. Provide visible options to compare independent sources, question an answer and pause a purchase when evidence is incomplete.
4. Evaluate confidence jointly with accuracy, claim verification and actual transaction outcomes to detect misplaced assurance.
5. Analyse environmental buying, environmental avoidance, social avoidance and premium payment separately so that practical decisions reflect domain-specific evidence.

5 5 Suggestions for future research

1. Check dataset with eligibility, consent, recruitment flow, exclusions and follow-up retention recorded before analysis.
2. Conduct expert review and cognitive interviews, then use independent developmental and confirmatory samples to evaluate the revised instrument.
3. Use longitudinal or experimental designs that establish literacy before a current comparison, confidence before the purchase, and behaviour after an appropriate follow-up interval.
4. Preregister the primary outcomes, component hypotheses, multiplicity rules, missing-data strategy and smallest substantively relevant effects.
5. Test the framework across product categories and population groups, with adequate power for planned comparisons and verification of measurement comparability.

6 CONCLUSION

This paper examined a multidimensional framework connecting digital literacy, decision confidence and four sustainable-shopping outcomes. Within the dataset, technical literacy was positively associated with confidence, and confidence was positively associated with every outcome after multiplicity adjustment. The four technical-literacy indirect associations also met the adjusted interval criterion. Cognitive and socio-emotional literacy did not meet that indirect-effect criterion, although selected nominal total and conditional associations were positive. The evidence therefore supported H3 across all four outcomes and provided mixed component support for H1, H2 and H4. Preserving that distinction was necessary for a faithful account of the numerical results. The framework and questionnaire offer a structured basis for a subsequent empirical study, but the present analysis did not establish observed consumer behaviour, population effects or causal mediation. Its value lies in the explicit construct map, aligned decision rules and separation of behavioural domains, which can be tested using a documented field dataset and independently validated measures.

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