

From Decision Resources to Effective Choices: The Mediating Role of Decision-Making Style and the Boundary Effect of Age among Indian Consumers

Gargi Dasgupta^{1*}, Dr. D N Murthy²

^{1*} Research Scholar, Department of Management Studies, IFIM, Bangalore

² Dean (Marketing & Research) Welingkar Institute of Management Development and Research, Bangalore

Abstract

Digital consumer environments expose individuals to extensive product information, technology-enabled comparison tools, and socially generated cues, yet access to these resources does not guarantee effective choice. This study develops and tests a decision-resource framework that explains how prior knowledge, technology adoption, and social influence shape consumer decision effectiveness through decision-making style, while age acts as a boundary condition. A quantitative, cross-sectional survey was conducted with 413 consumers drawn from five age groups. The model was estimated using partial least squares structural equation modelling with 5,000 bootstrap subsamples. The measurement model demonstrated satisfactory indicator reliability, internal consistency, convergent validity, discriminant validity, and acceptable collinearity. Prior knowledge, social influence, and technology adoption had significant positive effects on both decision-making style and decision effectiveness. Technology adoption showed the strongest direct effect on decision effectiveness and the strongest effect on decision-making style. Decision-making style positively influenced decision effectiveness and partially mediated all three antecedent relationships. Age significantly moderated the decision-making style to effectiveness relationship, indicating that the conversion of a structured decision process into effective choice varies across age groups. The model explained 71.4% of the variance in decision-making style and 89.9% of the variance in decision effectiveness. The study contributes by integrating cognitive, digital, and social decision resources within a single process model and by positioning decision-making style as a resource-conversion mechanism rather than a descriptive consumer trait.

Keywords: consumer decision-making; prior knowledge; technology adoption; social influence; decision-making style; age

Introduction

Consumer choice is increasingly formed within an information environment in which personal experience, digital interfaces, online reviews, peer recommendations, and platform-generated comparisons operate at the same time. Traditional accounts of consumer decision-making describe a sequence of need recognition, information search, evaluation, choice, and post-purchase assessment. That sequence remains useful, yet the conditions under which consumers move through it have changed. Search engines, marketplaces, social media, review systems, mobile applications, and recommendation tools have reduced the cost of information access while increasing the volume and diversity of decision cues. The central research problem is no longer limited to whether consumers can obtain information. It concerns whether they can convert multiple forms of decision support into a coherent process that produces accurate, confident, rational, and satisfactory choices.

Three decision resources are especially relevant to this conversion problem. Prior knowledge gives consumers a cognitive base for interpreting claims, identifying diagnostic attributes, and reducing uncertainty. Technology adoption provides access to digital search, comparison, review, and transaction capabilities. Social influence supplies experiential and normative information through family, peers, reviews, digital communities, and other reference sources. Each resource can strengthen consumer choice, but each may also increase complexity when it is not integrated into a clear decision routine. Recent work on emerging retail technologies shows that digital technologies reshape the consumer decision process rather than simply adding another information channel

(Sharma et al., 2023). Research on older consumers also indicates that technology acceptance, social influence, and learning can operate differently across age groups (Erjavec & Manfreda, 2022; Jang et al., 2024).

Prior studies have often examined knowledge, technology, social influence, and demographic differences as separate predictors of attitudes, intentions, adoption, or purchase outcomes. This fragmented treatment leaves an important process question unresolved: through what behavioural mechanism are cognitive, digital, and social resources translated into effective consumer decisions? Decision-making style offers a theoretically meaningful answer because it reflects the manner in which consumers compare alternatives, evaluate product features, allocate time to choice, and follow a structured pattern. In this view, decision-making style is not only a consumer characteristic. It is the process through which available resources are organised and applied.

A second unresolved issue concerns age. Age is frequently used to divide consumers into descriptive segments or to predict technology adoption. Such treatment may conceal its more important role as a boundary condition. Consumers at different life stages may vary in accumulated experience, familiarity with digital tools, trust formation, cognitive effort, and the sources they use to validate a choice. The same structured decision routine may not yield an identical level of effectiveness for all age groups. Treating age as a moderator offers a process-oriented explanation of heterogeneity and avoids reducing age to a simple profile variable.

This study addresses these issues using data from 413 Indian consumers across five age groups. It tests an integrated model in which prior knowledge, technology adoption, and social influence predict decision-making style and consumer decision effectiveness; decision-making style acts as a mediator; and age moderates the relationship between decision-making style and effectiveness. The study makes three contributions. First, it develops a decision-resource perspective that integrates cognitive, digital, and social inputs within one explanatory framework. Second, it positions decision-making style as a resource-conversion mechanism that explains how those inputs become effective choices. Third, it treats age as a boundary condition on the decision process rather than as a static segmentation label. The resulting model offers a concise explanation of how contemporary consumers combine what they know, the technologies they use, and the social information they receive to reach effective purchase outcomes.

Theoretical Background and Hypothesis Development

Decision resources and consumer decision effectiveness

Consumer decision effectiveness refers to the perceived quality of the decision process and its outcome, expressed through confidence, suitability, rationality, accuracy, and satisfaction with the final choice. Classical consumer models treat choice as a problem-solving process in which information is acquired, interpreted, compared, and converted into action (Bettman, 1979; Howard & Sheth, 1969; Payne et al., 1993). Contemporary consumer environments expand the sources available for this process. The consumer may draw on stored knowledge, technology-assisted information, and social evidence during the same purchase episode.

These sources can be interpreted as decision resources. Prior knowledge is an internal cognitive resource. Technology adoption is an enabling digital resource that expands search and comparison capability. Social influence is a relational resource that supplies information, reassurance, norms, and experiential cues. The value of each resource depends partly on the consumer's ability to organise it during evaluation. This logic creates a distinction between decision resources and decision process. The present study uses decision-making style to represent the process through which resources are translated into decision effectiveness.

Prior knowledge as a cognitive decision resource

Prior knowledge develops through earlier product exposure, accumulated experience, category familiarity, and stored information. Brucks (1985) and Alba and Hutchinson (1987) show that consumer expertise affects search, attribute interpretation, and the ability to distinguish relevant from

less useful cues. Knowledge can reduce uncertainty because consumers enter a purchase situation with a framework for judging alternatives rather than evaluating every option from the beginning. Knowledge should also shape decision-making style. Consumers with stronger prior knowledge can compare alternatives more systematically, recognise meaningful attributes, and use previous experience to screen information. A structured decision pattern gives consumers a route for applying what they know. Prior knowledge should also contribute directly to decision effectiveness because familiarity can improve confidence and fit between needs and chosen alternatives.

H1a: Prior knowledge positively influences decision-making style.

H1b: Prior knowledge positively influences consumer decision effectiveness.

Technology adoption as digital decision infrastructure

Technology adoption reflects the consumer's willingness and ability to use digital tools during search, comparison, evaluation, and purchase. Technology acceptance research shows that perceived usefulness, ease of use, and social context shape adoption and usage behaviour (Davis, 1989; Venkatesh et al., 2003). In consumer markets, technology extends beyond transaction convenience. It provides comparison interfaces, product filters, review access, price visibility, personalised recommendations, and rapid retrieval of alternatives.

Emerging digital technologies can alter the path through which consumers evaluate options and can make the process less linear (Sharma et al., 2023). Technology can strengthen decision-making style when consumers use digital resources to compare features, revisit alternatives, verify claims, and organise information. It can also improve effectiveness by reducing search cost and increasing access to decision-relevant information. Evidence from social media and digital service research supports the importance of technology-enabled information in consumer adoption and evaluation processes (Sharma et al., 2022).

H2a: Technology adoption positively influences decision-making style.

H2b: Technology adoption positively influences consumer decision effectiveness.

Social influence as a relational decision resource

Consumers rarely make choices in complete isolation. Family members, peer groups, online reviewers, influencers, digital communities, and prior users provide information that can shape evaluation. Social influence may be informational, when consumers use others' experiences as evidence, or normative, when choices are shaped by expectations and social acceptance (Deutsch & Gerard, 1955; Park & Lessig, 1977). Reference-group research also shows that the relevance of social sources varies by product, situation, and consumer characteristics (Bearden & Etzel, 1982).

Social inputs can shape decision-making style by directing attention to certain attributes, risks, brands, or alternatives. Reviews and recommendations may provide shortcuts, but they can also stimulate deeper comparison when consumers treat them as evidence to be checked against other information. Research on senior technology acceptance shows that informational and normative influence can have distinct roles in learning and adoption (Jang et al., 2024). Social influence should also contribute to effectiveness when trusted experience reduces uncertainty and improves confidence in the selected option.

H3a: Social influence positively influences decision-making style.

H3b: Social influence positively influences consumer decision effectiveness.

Decision-making style as a resource-conversion mechanism

Decision-making style captures the habitual orientation with which consumers approach choice. Consumer Styles Inventory research identifies systematic differences in quality consciousness, brand orientation, price consciousness, impulsiveness, confusion, and habitual choice (Sproles & Kendall, 1986). Later research links decision styles with product involvement and purchase behaviour (Bauer et al., 2006; Lysonski et al., 1996). The present study focuses on a structured and evaluative style characterised by comparison of alternatives, assessment of features and benefits, sufficient evaluation time, and a clear decision pattern.

A structured decision style should improve decision effectiveness because it governs the way information is processed. It encourages consumers to compare options, align features with needs, and reduce reliance on isolated cues. More importantly, it can transmit the effects of decision resources. Prior knowledge becomes useful when applied during evaluation. Technology creates value when its tools are used to support comparison. Social information contributes when it is interpreted within a coherent decision routine. This process logic supports a mediating role for decision-making style.

H4: Decision-making style positively influences consumer decision effectiveness.

H5a: Decision-making style mediates the relationship between prior knowledge and consumer decision effectiveness.

H5b: Decision-making style mediates the relationship between technology adoption and consumer decision effectiveness.

H5c: Decision-making style mediates the relationship between social influence and consumer decision effectiveness.

Age as a boundary condition

Age may alter how consumers acquire, value, and apply decision resources. Life-span perspectives suggest that goals, experience, cognitive strategies, and information preferences change across age (Carstensen et al., 1999). Technology studies also show that age can shape technology acceptance and usage patterns (Morris & Venkatesh, 2000). Recent research with older consumers indicates that online shopping adoption and digital service acceptance involve distinctive combinations of performance expectations, social information, learning, and perceived difficulty (Erjavec & Manfreda, 2022; Jang et al., 2024).

This study treats age as a moderator of the link between decision-making style and effectiveness. The purpose is not to assume that one age group is inherently more rational or more capable than another. It is to test whether a structured decision process translates into effective outcomes with equal strength across age groups. Differences in experience, digital familiarity, trust, and evaluation preferences create a basis for expecting variation in that relationship.

H6: Age moderates the positive relationship between decision-making style and consumer decision effectiveness.

Method

Research design, sample, and data collection

The study adopted a quantitative, descriptive, and causal research design. Primary data were collected through a structured questionnaire from consumers who had experience making purchase decisions. Convenience sampling was used to obtain participation from varied age categories and shopping backgrounds. The final sample contained 413 valid responses, a size suitable for estimating the proposed PLS-SEM model with multiple latent constructs, mediation, and moderation.

The age distribution was deliberately broad: 19.9% of respondents were below 25 years, 23.2% were 25 to 34, 21.3% were 35 to 44, 18.6% were 45 to 54, and 16.9% were 55 years and above. The sample included 51.6% male, 47.2% female, and 1.2% respondents identifying in another gender category. Shopping behaviour was mixed: 21.5% primarily shopped offline, 32.0% primarily shopped online, and 46.5% used both channels. This distribution offered sufficient variation for examining a decision model across age groups and shopping modes.

Measures

All multi-item constructs were measured on five-point Likert scales ranging from 1 = strongly disagree to 5 = strongly agree. The measures were adapted from established consumer behaviour and technology literature and adjusted to fit the study context. Prior knowledge contained five items capturing product knowledge, previous experience, comparison ability, confusion reduction, and perceived decision quality, drawing on Brucks (1985) and Alba and Hutchinson (1987). Technology adoption contained five items assessing the use of digital tools, online comparison, reliance on online

information, comfort with technology, and perceived improvement in purchase decisions, drawing on Davis (1989), Rogers (2003), and Venkatesh et al. (2003).

Social influence contained five items addressing family opinions, peers, reviews and recommendations, social media and digital communities, and others' experiences, based on reference-group and social influence literature (Bearden & Etzel, 1982; Deutsch & Gerard, 1955; Park & Lessig, 1977). Decision-making style contained five items measuring careful comparison, feature and benefit evaluation, systematic selection, sufficient evaluation time, and a clear decision pattern, drawing on Sproles and Kendall (1986) and later consumer-style work. Consumer decision effectiveness contained five items assessing satisfaction with outcomes, confidence in final choices, accuracy and need fit, rational evaluation, and perceived effectiveness of the decision process, grounded in classical decision-process research (Bettman, 1979; Howard & Sheth, 1969; Payne et al., 1993). Age group was modelled as the moderator.

Analytical procedure

Partial least squares structural equation modelling was performed in SmartPLS. The analysis proceeded in two stages. The measurement model was assessed using outer loadings, Cronbach's alpha, composite reliability, average variance extracted, the heterotrait-monotrait ratio, the Fornell-Larcker criterion, and variance inflation factors. The structural model was assessed using path coefficients, t-values, p-values, R-squared values, specific indirect effects, and the age interaction term.

Bootstrapping with 5,000 subsamples was used to test the significance of direct, indirect, and moderating effects. PLS-SEM was appropriate because the model contains multiple latent constructs and simultaneously tests direct effects, mediation, and moderation. Current methodological guidance also supports careful assessment of both measurement quality and structural relationships in marketing applications of PLS-SEM (Ringle et al., 2022).

Results

Measurement model

The measurement model met the required standards for reliability and convergent validity. All indicator loadings exceeded 0.70, ranging from 0.726 to 0.917. Cronbach's alpha values ranged from 0.866 to 0.926, composite reliability values from 0.903 to 0.944, and AVE values from 0.653 to 0.773. These results indicate strong internal consistency and adequate convergence among the indicators of each construct.

Table 1. Measurement model assessment

Construct	Loading range	Alpha	rho_A	rho_C	AVE
Decision-making style	0.819-0.895	0.906	0.907	0.930	0.726
Decision effectiveness	0.844-0.917	0.926	0.929	0.944	0.773
Prior knowledge	0.822-0.889	0.912	0.916	0.934	0.740
Social influence	0.726-0.880	0.866	0.878	0.903	0.653
Technology adoption	0.819-0.857	0.893	0.893	0.921	0.700

Discriminant validity was established using HTMT and the Fornell-Larcker criterion. HTMT values were below 0.90; the highest reported values were 0.841 for decision effectiveness with decision-making style, 0.814 for social influence with decision effectiveness, and 0.808 for technology adoption with decision-making style. The square root of AVE for each construct exceeded its correlations with the remaining constructs. Structural VIF values ranged from 1.321 to 3.499, indicating no serious collinearity concern for interpretation of the path model. Model fit statistics were consistent across the estimated models. SRMR ranged from 0.059 to 0.065. NFI ranged from 0.874 to 0.893. These values support interpretation of the structural estimates while recognising that PLS-SEM places primary emphasis on explanatory and predictive relationships rather than reliance on a single global fit index.

Direct effects

All direct structural relationships were positive and statistically significant. Technology adoption was the strongest predictor of consumer decision effectiveness ($\beta = 0.462$, $t = 9.706$, $p < .001$), followed by prior knowledge ($\beta = 0.362$, $t = 7.735$, $p < .001$) and social influence ($\beta = 0.320$, $t = 7.045$, $p < .001$). Technology adoption also produced the strongest effect on decision-making style ($\beta = 0.416$, $t = 5.551$, $p < .001$), followed by social influence ($\beta = 0.355$, $t = 4.489$, $p < .001$) and prior knowledge ($\beta = 0.268$, $t = 4.622$, $p < .001$). Decision-making style had a positive effect on decision effectiveness ($\beta = 0.294$, $t = 4.229$, $p < .001$).

Table 2. Structural path results

Path	Beta	t	p	Decision
Prior knowledge -> Decision-making style	0.268	4.622	< .001	Supported
Technology adoption -> Decision-making style	0.416	5.551	< .001	Supported
Social influence -> Decision-making style	0.355	4.489	< .001	Supported
Prior knowledge -> Decision effectiveness	0.362	7.735	< .001	Supported
Technology adoption -> Decision effectiveness	0.462	9.706	< .001	Supported
Social influence -> Decision effectiveness	0.320	7.045	< .001	Supported
Decision-making style -> Decision effectiveness	0.294	4.229	< .001	Supported

Mediation, moderation, and explanatory power

Decision-making style significantly mediated all three antecedent relationships. The indirect effect of prior knowledge on decision effectiveness through decision-making style was $\beta = 0.079$ ($t = 3.072$, $p = .002$). The indirect effect of social influence was $\beta = 0.104$ ($t = 3.144$, $p = .002$). The strongest indirect effect was technology adoption through decision-making style, $\beta = 0.122$ ($t = 3.253$, $p = .001$). Because the direct effects of all three antecedents remained significant, the results indicate partial mediation. Age significantly moderated the relationship between decision-making style and decision effectiveness. The interaction effect was $\beta = 0.177$ ($t = 4.424$, $p < .001$). The positive interaction confirms that the strength of the decision-making style to effectiveness relationship varies across age categories. The available model establishes moderation but does not provide pairwise age-group path comparisons, so interpretation is limited to the presence and direction of moderation rather than claims that a specific age group has the strongest path. The model explained 71.4% of the variance in decision-making style (adjusted R-squared = 0.705) and 89.9% of the variance in consumer decision effectiveness (adjusted R-squared = 0.893). The high explanatory values indicate that the selected cognitive, digital, social, and process variables account for a substantial share of variation within the sample.

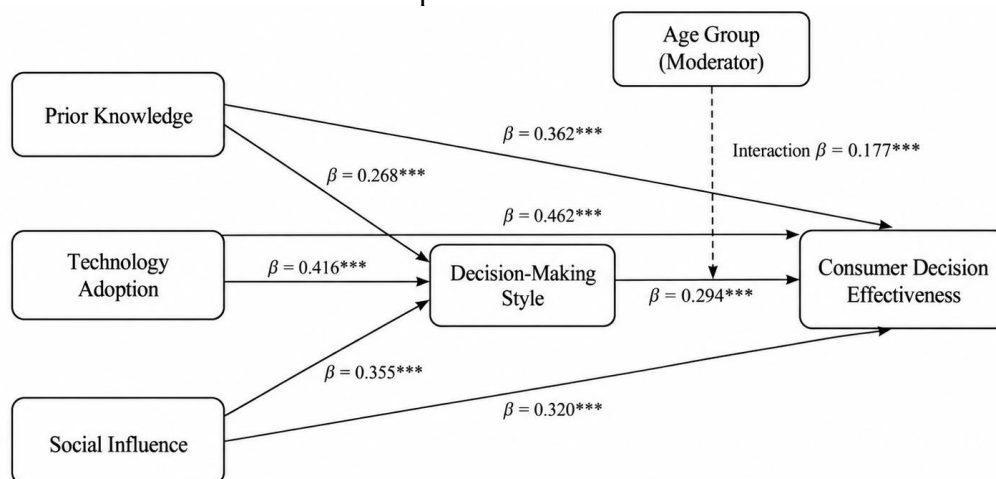


Figure 1. Structural Model Results of the Proposed Consumer Decision-Making Framework
Table 3. Mediation, moderation, and explanatory power

Effect	Beta	t	p	Interpretation
Prior knowledge -> DMS -> Effectiveness	0.079	3.072	.002	Partial mediation
Social influence -> DMS -> Effectiveness	0.104	3.144	.002	Partial mediation
Technology adoption -> DMS -> Effectiveness	0.122	3.253	.001	Partial mediation
Age x DMS -> Effectiveness	0.177	4.424	< .001	Significant moderation
R-squared: Decision-making style	0.714			Strong explanatory power
R-squared: Decision effectiveness	0.899			Strong explanatory power

Discussion

The results support a process view of consumer decision-making in which effectiveness depends on both the resources available to the consumer and the way those resources are organised. Prior knowledge, technology adoption, and social influence each contributed to decision-making style and to decision effectiveness. The pattern suggests that contemporary choice is neither purely cognitive nor purely technology-driven. It is produced through the interaction of stored knowledge, digital support, relational information, and a behavioural routine for evaluating alternatives. Technology adoption was the strongest predictor in both structural routes. Its direct effect on decision effectiveness was $\beta = 0.462$, and its effect on decision-making style was $\beta = 0.416$. This finding extends technology acceptance logic from adoption intention toward decision quality. Digital tools matter because they can change the work that consumers perform during choice. Search, filtering, side-by-side comparison, review access, price visibility, and rapid switching among alternatives can support a more structured evaluation routine. Sharma et al. (2023) similarly argue that emerging retail technologies reshape consumer decision processes. The present results add evidence that technology is most useful when it operates as decision infrastructure rather than as a simple transaction channel. Prior knowledge also made a substantial contribution. Its direct effect on decision effectiveness and its indirect effect through decision-making style indicate that accumulated experience serves two functions. It provides immediate interpretive value and it supports a more disciplined comparison process. This is consistent with consumer expertise research in which knowledge affects the search and use of product information (Alba & Hutchinson, 1987; Brucks, 1985). The result is especially relevant in information-rich markets. More information is not equivalent to better understanding. Consumers need a knowledge base that allows them to distinguish useful attributes from persuasive but weak signals. Social influence affected both decision style and effectiveness. This result supports a socially embedded view of consumer choice. Family advice, peer experience, reviews, and digital communities can reduce uncertainty and provide cues that consumers may not obtain through direct experience. The result also calls for caution in managerial interpretation. A positive social influence coefficient does not imply that all forms of social persuasion improve decision quality. Authentic reviews and credible recommendations may support evaluation, while manipulated reviews, undisclosed endorsements, and pressure-based influence may distort it. The theoretical value of social influence lies in its informational and relational role within the decision process. The mediation results provide the clearest theoretical insight. Decision-making style partially transmitted the effects of all three resources. This means that decision resources do not operate only as direct inputs. They also work by shaping the consumer's method of comparison and evaluation. The strongest mediated pathway was technology adoption through decision-making style. Digital access appears to create greater value when consumers use it to establish a structured process. This finding supports the proposed interpretation of decision-making style as a resource-conversion mechanism. It moves the construct beyond consumer typology and gives it a functional position between resources and outcomes. The age interaction extends the model by showing that the effectiveness of a structured decision style is not uniform across age categories. This finding is compatible with life-span and technology adoption research, which indicates that experience, goals, digital familiarity, and information preferences can change with age (Carstensen et al., 1999; Morris & Venkatesh, 2000). Studies of older consumers also show that

technology learning and social influence can operate differently in digital settings (Erjavec & Manfreda, 2022; Jang et al., 2024). The present result should be read as evidence of heterogeneity in the process rather than as a basis for age stereotypes. The study does not establish that younger consumers are more effective digital decision makers or that older consumers rely more heavily on experience. It establishes that age changes the strength of the link between decision style and effectiveness.

Theoretical Contributions

The first contribution is the integration of prior knowledge, technology adoption, and social influence as three forms of decision resources. Existing streams often treat these variables within separate literatures on expertise, technology acceptance, or reference groups. The integrated framework shows that cognitive, digital, and relational resources can be analysed within one consumer decision architecture. This structure offers a clearer explanation of contemporary choice environments in which these inputs are encountered together. The second contribution is the process role assigned to decision-making style. Consumer-style research has traditionally used decision styles to classify consumers or explain behavioural tendencies. The present model shows that a structured decision style also functions as a mechanism that carries part of the effects of knowledge, technology, and social information into decision effectiveness. This resource-conversion view distinguishes what consumers have access to from how they use it. The third contribution is the treatment of age as a boundary condition. Age is frequently included as a descriptive demographic variable or direct predictor. The moderation result shows that age can alter the strength of a central behavioural relationship. This offers a more theoretically useful role for age because it helps explain when a structured decision process translates more strongly into effective choice.

Managerial and Policy Implications

Managers should design digital environments around decision quality rather than information volume. Comparison pages should use consistent attributes, filters should reflect consumer needs, prices and return conditions should be visible, and recommendation systems should provide understandable reasons for suggestions. These features can strengthen the technology-to-decision-style pathway by helping consumers organise information rather than simply exposing them to more content. Product information should be designed to build usable prior knowledge. Technical descriptions can be paired with plain-language explanations, examples, comparison cues, warranties, and need-based guidance. Consumer education initiatives can teach comparison, source evaluation, and verification skills. These interventions are especially useful when products are complex or when consumers face unfamiliar digital environments. Review and recommendation systems should protect the credibility of social information. Verified-purchase indicators, disclosure of incentives, moderation of fraudulent reviews, and transparent influencer relationships can preserve the informational value of social influence. Firms should also avoid rigid age segmentation. Interfaces can offer flexible levels of detail, assisted and self-service pathways, readable design, multiple support channels, and optional human help. Age-sensitive design is most useful when it expands choice architecture without assuming uniform ability within an age group.

Limitations and Future Research

The study has four main limitations. First, the cross-sectional design does not establish temporal causality. Longitudinal and experimental studies could test whether changes in technology use or consumer knowledge lead to later changes in decision style and effectiveness. Second, the measures are self-reported and collected from the same questionnaire, creating a possibility of common method bias despite acceptable reliability, validity, and collinearity diagnostics. Future research can combine behavioural data, observed search patterns, transaction records, or time-separated measures. Third, convenience sampling limits population-level generalisation. Replication with probability-based or stratified samples across regions and product categories would strengthen external validity. Fourth, age was tested as an interaction term, but the available analysis does not include

measurement invariance and pairwise multigroup comparisons. Future work should examine age-group differences through MICOM and PLS-MGA or permutation procedures before making group-specific claims. Predictive assessment using holdout procedures such as PLSpredict could also complement explanatory evaluation in later replications (Shmueli et al., 2019).

Conclusion

Effective consumer choice depends on more than access to information. It depends on the resources consumers bring to the decision and the process through which those resources are applied. Using data from 413 consumers, this study shows that prior knowledge, technology adoption, and social influence each improve decision-making style and decision effectiveness. Decision-making style carries part of these effects, demonstrating its role as a resource-conversion mechanism. Age changes the strength of the relationship between decision style and effectiveness, positioning it as a meaningful boundary condition. The findings support a consumer decision framework in which knowledge provides cognitive structure, technology provides digital capability, social influence provides relational evidence, and decision-making style connects these resources to effective choice.

References

- Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of Consumer Research*, 13(4), 411-454.
- Bauer, H. H., Sauer, N. E., & Becker, C. (2006). Investigating the relationship between product involvement and consumer decision-making styles. *Journal of Consumer Behaviour*, 5(4), 342-354.
- Bearden, W. O., & Etzel, M. J. (1982). Reference group influence on product and brand purchase decisions. *Journal of Consumer Research*, 9(2), 183-194.
- Bettman, J. R. (1979). *An information processing theory of consumer choice*. Addison-Wesley.
- Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research*, 12(1), 1-16.
- Carstensen, L. L., Isaacowitz, D. M., & Charles, S. T. (1999). Taking time seriously: A theory of socioemotional selectivity. *American Psychologist*, 54(3), 165-181.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.
- Deutsch, M., & Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment. *Journal of Abnormal and Social Psychology*, 51(3), 629-636.
- Erjavec, J., & Manfreda, A. (2022). Online shopping adoption during COVID-19 and social isolation: Extending the UTAUT model with herd behavior. *Journal of Retailing and Consumer Services*, 65, 102867. <https://doi.org/10.1016/j.jretconser.2021.102867>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115-135.
- Howard, J. A., & Sheth, J. N. (1969). *The theory of buyer behavior*. Wiley.
- Hoyer, W. D., MacInnis, D. J., & Pieters, R. (2010). *Consumer behavior* (5th ed.). Cengage Learning.
- Jang, H. W., Moon, C., Jung, H. S., Cho, M., & Bonn, M. A. (2024). Normative and informational social influence affecting digital technology acceptance of senior restaurant diners: A technology learning perspective. *International Journal of Hospitality Management*, 116, 103626. <https://doi.org/10.1016/j.ijhm.2023.103626>
- Kozinets, R. V., de Valck, K., Wojnicki, A. C., & Wilner, S. J. S. (2010). Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of Marketing*, 74(2), 71-89.
- Lyonski, S., Durvasula, S., & Zotos, Y. (1996). Consumer decision-making styles: A multi-country investigation. *European Journal of Marketing*, 30(12), 10-21.

- Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. *Personnel Psychology*, 53(2), 375-403.
- Park, C. W., & Lessig, V. P. (1977). Students and housewives: Differences in susceptibility to reference group influence. *Journal of Consumer Research*, 4(2), 102-110.
- Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press.
- Ringle, C. M., Sarstedt, M., Sinkovics, N., & Sinkovics, R. R. (2022). A perspective on using partial least squares structural equation modelling in data articles. *Data in Brief*, 48, 109074.
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Sharma, M., Banerjee, S., & Paul, J. (2022). Role of social media on mobile banking adoption among consumers. *Technological Forecasting and Social Change*, 180, 121720. <https://doi.org/10.1016/j.techfore.2022.121720>
- Sharma, P., Ueno, A., Dennis, C., & Paydas Turan, C. (2023). Emerging digital technologies and consumer decision-making in retail sector: Towards an integrative conceptual framework. *Computers in Human Behavior*, 148, 107913. <https://doi.org/10.1016/j.chb.2023.107913>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322-2347.
- Sproles, G. B., & Kendall, E. L. (1986). A methodology for profiling consumers' decision-making styles. *Journal of Consumer Affairs*, 20(2), 267-279.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478.
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178.
- Bruine de Bruin, W., Parker, A. M., & Fischhoff, B. (2007). Individual differences in adult decision-making competence. *Journal of Personality and Social Psychology*, 92(5), 938-956.